

# **THE DYNAMIC PREDICTION OF COMPANY FAILURE – THE INFLUENCE OF TIME, THE ECONOMY AND NON-LINEARITY**

Maria Heui-Yeong Kim

A thesis submitted in fulfilment of  
the requirements for the degree of

Doctor of Philosophy



Discipline of Finance  
Faculty of Business and Economics  
University of Sydney  
Australia

June 2011

## **STATEMENT OF ORIGINALITY**

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

.....

Maria Heui-Yeong Kim

*To my Lord who saved me.*

*May You be glorified.*

*To my beloved parents.*

*May this bring honour to you.*

*Though it can hardly reciprocate all your sacrifice.*

## **ACKNOWLEDGEMENTS**

I would like to give my deepest gratitude to Associate Professor Graham Partington, who has always been the best supervisor throughout the process of my Ph.D. This thesis would not have been possible without his expert guidance and support. I am deeply grateful to Graham for his constant encouragement and sincere belief in my abilities. Not only has he been my great academic advisor, but he has always been my best mentor and a constant source of support.

I am greatly indebted to Dr. Giang Truong who has offered her genuine interest in my work, helpful advices and valuable time. This thesis greatly benefited from her wisdom, experiences and support. I also gratefully acknowledge Dr. Philip Gharghori for his constructive comments and ideas.

This thesis has also benefited from the assistance, both financial and practical of an industry participant and organisations. I am grateful for research scholarship provided by the Commonwealth Government (Australian Postgraduate Award), Capital Markets Co-operative Research Centre (CMCRC) and the Finance Discipline of the Faculty of Economics and Business at the University of Sydney. The Securities Industry Research Centre for Asia Pacific is also acknowledged for the provision of data. Especially, I would like to give special thanks to the CMCRC for offering me a wonderful opportunity to work for an Industry partner, Royal Bank of Scotland (former ABN AMRO) during my Ph.D. candidature.

I am also grateful to my colleagues and friends, in particular Dr. Aelee Jun, Dr. Giang Truong, Dr. Sarah Kim, Dr. Hongyan Gu, Dr. Adam Lockyer, Elisabeth Huynh,

Dr. Jennifer Kruk, Qian Chen, Simon Leung and Shin-Wook An. I have appreciated their companionship, friendship, encouragement, and earnest support during this special period in my life.

My church family are worthy of special mention, especially Pastor Seung-Bae Kim and his wife, Sun Ju Lee. I express my heartfelt thanks for their ceaseless prayers and unconditional love. To all my brothers and sisters who have prayed and supported me for this study, in particular Jong-Boon Lee, Linda Ham, Alan Kim, Mihee Cho, Lina Park, Hanna So, Richard Gong, Albert Lee, and Kieren Lim, I am sincerely thankful for their earnest prayers and invaluable fellowship. Special thanks go to Sister Jane Lee and Sarah Jung for great assistance with editing and proofreading. Indeed, I would like to express my sincere appreciation to Dr. Paul Yoo, who has lavishly supported me, both personally and spiritually.

My greatest debt is to my beloved family who have walked along this journey right beside me and continually inspired me to move forward. To my much respected parents, Mae-Sik Kim and Kyung-Soon Lee, my beautiful sister Ji-Yeong Kim, her perfect husband Seok-Moon Jung, and my lovely brother Woo-Jin Kim, words cannot express my gratitude for your dedicated love and endless support for all my life.

Finally, I thank my heavenly Father who has directed my path and led me all the way. With no doubt, this has been possible with the strength and power provided by You. I give You all the glory, my faithful Lord.

## **ABSTRACT**

Dynamic forecasts of financial distress have received far less attention than static forecasts, particularly in Australia. This thesis, therefore, investigates dynamic probability forecasts for Australian firms. Novel features of the modelling are the use of time-varying variables in forecasts from a Cox model and allowing for non-linearity between financial distress and predictor variables.

Cox regression models with time-varying variables are used to estimate the survival probabilities of a large sample of Australian listed companies. Not only is this one of relatively few studies to apply dynamic variables in forecasting financial distress, but to the author's knowledge it is the first to provide forecasts of survival probabilities using the Cox model with time-varying variables. Forecast accuracy is evaluated using receiver operating characteristics curves and the Brier Score. It was found that the models had predictive power in out-of-sample forecast. Allowing for non-linearity between the predictor variables and financial distress risk substantially improved out-of-sample accuracy in discriminating between distressed and non-distressed firms. However, variables capturing the state of the economy did not substantively improve the predictive power of the model.

# TABLE OF CONTENTS

<b>STATEMENT OF ORIGINALITY.....</b>	<b>I</b>
<b>ACKNOWLEDGEMENTS.....</b>	<b>III</b>
<b>ABSTRACT .....</b>	<b>V</b>
<b>LIST OF FIGURES.....</b>	<b>X</b>
<b>LIST OF TABLES.....</b>	<b>XI</b>
<b>CHAPTER 1: INTRODUCTION.....</b>	<b>1</b>
1.1 Introduction.....	1
1.2 Objectives of the Thesis.....	3
1.3 The Use of the Cox Model.....	6
1.4 Summary of Findings.....	7
1.5 Structure of the Thesis .....	8
<b>CHAPTER 2: REVIEW OF CORPORATE BANKRUPTCY PREDICTION ..</b>	<b>10</b>
2.1 Introduction.....	10
2.2 Background to Bankruptcy Prediction.....	10
2.2.1 Definition of Bankruptcy.....	10
2.2.2 The Use of Financial Ratios in Early Financial Distress Prediction.....	11
2.3 Reviews of Bankruptcy Prediction Models .....	12
2.3.1 Introduction to Bankruptcy Prediction Modelling.....	12
2.3.2 Early Bankruptcy Prediction Studies.....	13
2.3.3 Alternative Techniques .....	21
2.3.4 Models Analysing Longitudinal Data in Corporate Bankruptcy Prediction.....	25
2.4 Empirical Approaches to Predicting Corporate Failure at the Firm Level and the Macroeconomic Level.....	31
2.4.1 Accounting-Ratio-Based Models versus Market-Based Models.....	31

2.4.2	Macroeconomic Factors in Financial Distress Prediction .....	35
2.5	Non-Linear Approach to Corporate Failure Prediction .....	37
2.6	Measuring Model Accuracy – Problems and Resolutions.....	38
2.6.1	Problems of State Forecasts.....	38
2.6.2	Possible Remedies .....	40
2.7	Conclusion .....	40
<b>CHAPTER 3:</b>	<b>DATA AND METHODS .....</b>	<b>43</b>
3.1	Introduction.....	43
3.2	Model Construction .....	43
3.2.1	Cox Proportional Hazards Model .....	43
3.2.2	Partial Likelihood Function .....	46
3.3	Data.....	50
3.3.1	Sample Selection.....	50
3.3.2	Dependent Variables.....	54
3.3.3	Firm-Specific Variables.....	54
3.3.4	Summary Statistics .....	57
3.4	Model Evaluation Approaches.....	64
3.4.1	Discrimination and Precision.....	64
3.4.2	Receiver Operating Characteristics (ROC).....	64
3.4.3	Scoring Rule (Brier Score) .....	68
3.5	Conclusion .....	68
<b>CHAPTER 4:</b>	<b>PREDICTING FINANCIAL DISTRESS – WHICH</b>	
<b>APPROACH IS BEST? .....</b>	<b>.....</b>	<b>70</b>
4.1	Introduction.....	70
4.2	Multiple-Period versus Single-Period Models.....	71
4.2.1	Why is the Multiple-Period Approach Preferred? .....	71
4.2.2	Multiple-Period Model Construction.....	72
4.3	Accounting-Based versus Market-Based Variables .....	74
4.3.1	Do Market-Based Variables Predict the Company Failure Better? .....	74

4.3.2	Models with Accounting-Based and Market-Based Variables .....	74
4.4	Models with and without Lagged Changes.....	75
4.4.1	Is Company Failure a Sudden Event or a Historical Outcome? .....	75
4.4.2	Models with Lagged Changes of Predictor Variables .....	75
4.5	Data and Evaluation Methods.....	76
4.6	Results.....	76
4.6.1	Results for the First Two Research Questions.....	76
4.6.2	Results for the Third Research Question .....	84
4.7	Conclusion .....	87
<b>CHAPTER 5: TIME AND THE PREDICTION OF FINANCIAL DISTRESS.</b>		<b>89</b>
5.1	Introduction.....	89
5.2	A Cox Hazards Model with Time-Varying Covariates .....	91
5.2.1	Difficulties in Practical Application of a Dynamic Cox Model to Financial Distress Prediction .....	96
5.2.2	Integrated Baseline Hazard.....	97
5.2.3	Development of SAS Macro Program.....	98
5.3	Data and Evaluation Methods.....	98
5.4	Results.....	99
5.4.1	Model Estimation.....	99
5.4.2	Model Validation .....	105
5.5	Conclusions and Suggestions for Future Research.....	109
<b>CHAPTER 6: THE DYNAMIC PREDICTION OF COMPANY FAILURE – THE INFLUENCE OF THE ECONOMY AND NON-LINEARITY .....</b>		<b>111</b>
6.1	Introduction.....	111
6.2	Macroeconomic Risk Factors and the Prediction of Company Failure .....	113
6.2.1	Motivation.....	113
6.2.2	A Time-Varying Cox Hazards Model with Macroeconomic Control Variables .....	116
6.3	Non-Linear Relation between Company Failure and Predictor Variables ...	116

6.3.1	Why a Non-Linear Approach to Failure Risk Modelling? .....	116
6.3.2	A Time-Varying Cox Hazards Model with Non-Parametric Data Transformation Based on Failure Rates.....	119
6.4	Data and Evaluation Method .....	120
6.4.1	Macroeconomic Variables .....	120
6.5	Results.....	125
6.5.1	Model Estimation.....	125
6.5.2	Model Validation and Implication of Modelling with Macroeconomic Covariates and with a Non-Linear Approach .....	129
6.6	Conclusions.....	133
 <b>CHAPTER 7: CONCLUSIONS AND SUGGESTIONS FOR FUTURE</b>		
<b>RESEARCH .....</b>		
	<b>RESEARCH .....</b>	<b>134</b>
7.1	Summary of Findings.....	134
7.2	Contributions .....	139
7.3	Limitations and Suggestions for Future Research .....	140
 <b>REFERENCE .....</b>		
	<b>REFERENCE .....</b>	<b>142</b>
 <b>APPENDIX A: SAS MACRO PROGRAM FOR THE TIME-VARYING COX</b>		
<b>HAZARDS MODEL ESTIMATION .....</b>		
	<b>HAZARDS MODEL ESTIMATION .....</b>	<b>157</b>
 <b>APPENDIX B: SAS MACRO PROGRAM FOR MODEL EVALUATION OF</b>		
<b>PREDICTIVE ACCURACY USING RECEIVER OPERATING</b>		
<b>CHARACTERISTICS CURVE.....</b>		
	<b>CHARACTERISTICS CURVE.....</b>	<b>164</b>

## LIST OF FIGURES

Figure 2-1: A Typical Fully Connected Feed Forward Neural Network (MLP) Used for Two-Group Classification Problems (source from Zhang et al., 1999)	23
Figure 3-1: Calendar Time versus Event Time .....	48
Figure 3-2: Illustrative Receiver Operating Characteristic (ROC) Curve.....	67
Figure 4-1: ROC Curves.....	83
Figure 5-1: Estimation of the Likelihood for the Failure of Firm A in a Conventional Cox Proportional Hazards Model.....	92
Figure 5-2: Estimation of the Likelihood for the Failure of Firm A in a Cox Hazards Model with Time-Varying Covariates .....	95
Figure 6-1: Calendar Time versus Event Time .....	115
Figure 6-2: Non-Linear Relation between Predictor Variables and the Risk of Default .....	118

## LIST OF TABLES

Table 3-1: Data Sample .....	53
Table 3-2: Firm-Specific Predictor Variables Used in Previous Financial Distress Studies .....	56
Table 3-3: Descriptive Statistics of Firm-Specific Variables.....	59
Table 3-4: Correlation Matrix of Firm-Specific Variables .....	63
Table 3-5: Classification Matrix for Verification of a Binary Forecast System .....	65
Table 4-1: Single-Period Logit Model Estimates for <i>Model 1, 2</i> and <i>3</i> .....	79
Table 4-2: Multiple-Period Hazards Model Estimates for <i>Model 1, 2</i> and <i>3</i> .....	80
Table 4-3: Forecast Accuracy with the Area Under ROC Curve.....	82
Table 4-4: Hazards Model Estimates with Lagged Changes for <i>Model 1, 2</i> and <i>3</i> .....	85
Table 4-5: Forecast Accuracy with the Area Under ROC Curve.....	87
Table 5-1: Hazard Model Estimates .....	100
Table 5-2: The Time-Varying Risk Scores and Survival Probabilities of 20 Firms Selected From Estimation Sample .....	103
Table 5-3: Predictive Accuracy .....	107
Table 6-1: Macroeconomic Variables Used in Previous Financial Distress Studies	121
Table 6-2: Summary Statistics of Macroeconomic Variables.....	124
Table 6-3: Correlation Matrix .....	125
Table 6-4: Parameter Estimates and Model Fit Summary for <i>Model 1, 2, 3</i> and <i>4</i> ...	128
Table 6-5: Predictive Accuracy .....	132

# **CHAPTER 1: INTRODUCTION**

## **1.1 Introduction**

Each year, approximately one percent of all companies listed on the Australian Securities Exchange experience financial distress. In this study financial distress is defined as entering into voluntary administration, liquidation, or receivership or being delisted due to failure to pay annual listing fees. Estimating the probability of a firm experiencing financial distress is a critical task in the credit risk assessment process; however, there is no generally accepted model for predicting company failures. Nonetheless, there are landmarks in the search for a better model, for example, Altman's multivariate discriminant analysis (1968), Ohlson's logit analysis (1980) and Shumway's discrete hazards model (2001). Despite many decades of research since the pioneering work of Beaver (1966), the pursuit of alternative models to better estimate the probability of failure is ongoing.

One of the most widely used approaches in bankruptcy prediction is using a statistical method, such as Altman's Z-score model (1968). In such approaches, the relationship between a firm's failure and risk factors relating to its failure is usually modelled using financial statement data. Traditional statistical approaches mainly use a single year of observations for a firm's financial characteristics as input data. They focus on making a dichotomous decision at that given point in time as to whether the company will fail or not. The consequence is that the application of these single-

period static approaches may not be robust when they are applied to financial conditions other than those under which they were originally developed (Grice and Dugan, 2001).

The use of a hazards model in bankruptcy forecasting by Shumway (2001) caused a change in the direction of financial distress prediction modelling. Effectively, it set out an approach which changed the concept of the common static classification and turned it into a dynamic process where the financial performance of a company is evaluated over time, with the objective of giving failure probabilities over the company's lifetime (duration).

The thesis begins with the pursuit of dynamic prediction of a company failure. It aims to estimate the probability of failure with inclusion of the time dimension. This is done using survival analysis. The particular model used is Cox proportional hazards model (Cox, 1972). The survival analysis explicitly models the duration of time until the firm's failure. Thus, a time series of probabilities is generated that keeps track of the expected variation in failure risk over time. This technique does not appear to have received much attention in the finance literature until the publication of a comprehensive review of survival analysis applied to the study of financial distress by LeClere (2000). This thesis will model the dynamic path-to-failure as a function of time and various firm-specific characteristics, as well as economy-wide risk factors.

Survival analysis is an appropriate choice in defining the function of time and risk factors; however, dynamic forecasts of the failure probability for time  $t$  to  $t+n$  have received relatively less attention than static forecasts in the prior literature. This study addresses the challenge of forming time-varying forecasts with time-varying

covariates, thus tracking the changing probability of a firm's financial distress over time. To the author's knowledge, it is the first study to provide forecasts of survival probabilities using the Cox model with time-varying variables.

Another main contribution of the thesis is in development of non-linear modelling of financial distress. While it is reasonable to think that the risk of corporate failure does not necessarily relate linearly with predictor variables, prior literature in financial distress has paid very little attention to the effect of non-linearity on predicting the risk of corporate failure. The findings of the thesis are that allowing for non-linearity between the predictor variables and financial distress risk substantially improves out-of-sample forecast accuracy.

Much of the literature in this research conventionally uses the term bankruptcy prediction (for example, Altman, 1968; Ohlson, 1980; Shumway, 2001; Hillegeist, Keating, Cram and Lundstedt, 2004). Variations in terminology, such as company failure, are also used. For Australian studies the term financial distress prediction or failure prediction is often preferred.<sup>1</sup>

## **1.2 Objectives of the Thesis**

Building on the findings from previous financial distress studies, this thesis has three main objectives. Firstly, it aims to predict the event occurrence in a forward direction (prospectively), whereas many studies predefine the event and look in retrospect to find which variables differentiate between financially distressed and non-distressed firms. Consequently, the approach taken here examines the pattern of the

---

<sup>1</sup> Under Australian law, companies can enter voluntary administration, receivership or liquidation, whereas only individuals can go bankrupt.

risk factors (predictor variables) from the start of the observation period until the firm either fails or leaves the study.

A key feature of the thesis is the use of dynamic (time-varying) variables. This is motivated by a number of recent studies which proposed that when using hazards models a vector of time-series data should be treated as if they were represented as a single variable (Wheelock and Wilson, 2000; Partington, Russel, Stevenson and Torbey, 2001; Shumway, 2001; Chava and Jarrow, 2004; Nam, Kim, Park and Lee, 2008; Bonfim, 2009; Cole and Wu, 2009). This thesis uses both multiple-period data and time-varying variables. Multiple-period data allows the distress model to repeatedly observe a company through time and to use all of those observations. Time-varying variables treat multiple-period data as a single variable for each time series. For example, traditional bankruptcy studies would treat five years of returns on assets (ROA) as five variables. In contrast, this study treats such data as one time-varying variable whose values are dynamically updated. These variables are employed in modelling the failure probability of a large sample of Australian listed firms using the Cox (1972) hazards model.

Secondly, the thesis addresses the problem of making forecasts when dynamic (time-varying) variables are included in a Cox hazards model. The Cox model is a much used technique for estimating hazards models and is particularly convenient for estimating models with dynamic variables. However, forming forecasts is problematic when a Cox hazards model contains dynamic variables. There have been a couple of studies using a Cox hazards model with time-varying variables to *model* failure probabilities (for example, Wheelock and Wilson, 1995; Kim, Anderson, Amburgey

and Hickman, 1995). However, these studies could not overcome the technical difficulties of forming forecasts with dynamic variables. In this study, a new approach inspired by recent advances in medical research (Chen, Yen, Wu, Liao, Liou, Kuo, and Chen, 2005) is implemented to provide forecasts of failure probabilities with dynamic variables in a Cox hazards model.

Two approaches are used to evaluate the accuracy of failure prediction of the models. First, estimates of the failure probabilities are assessed for discriminative power using receiver operating characteristic (ROC) curves. Second, the Brier score is used to measure the model's precision.

Thirdly, the thesis aims to extend the scope of the forecast models by including the impact of macroeconomic variables and allowing for the impact of a non-linear relation between financial distress and the predictor variables. There is some evidence that macroeconomic data aids in forecasting the time-series variation in financial distress (Liu, 2004; Rösch and Scheule, 2005; Carling, Jacobson, Linde and Roszbach, 2007; Carling, Jacobson, Linde and Roszbach (2007); Nam, Kim, Park and Lee, 2008; Bellotti and Crook, 2009; Bonfim, 2009). However, some studies find no such evidence (Partington, Russel, Stevenson and Torbey, 2001; Cole and Wu, 2009). This thesis provides further empirical evidence on the effect of the inclusion of economy-wide variables on model performance.

Furthermore, the thesis also examines the possible non-linear relation between company failure and the predictor variables. Very little attention has been paid to investigating non-linear effects of firm characteristics on the risk of firm failure in prior financial distress studies. A recent exception is Chan, Faff, Gharghori and

Lajbcygier (2008), who use a non-linear technique called generalised additive models (GAMs). The last part of this thesis aims to develop a non-linear approach to modelling company failure, but uses a technique that is considerably simpler to implement than the GAMs approach.

### **1.3 The Use of the Cox Model**

Across disciplines, and particularly in medicine, the Cox hazards model (Cox, 1972) has been one of the most popular models for analysing survival data. In recent years, the use of the Cox hazards model has been increasing in the area of financial modelling and emphasis has been put on the use of time-varying covariates in survival models. One of the distinct benefits of the Cox hazards model relative to other methods is its ability to account for the effect of risk factors (predictor variables) on the duration of time until the event of interest occurs. It also allows the use of time-varying variables so that changes in the firm's financial characteristics can be incorporated into the estimation over time. This explains why survival analysis is preferred to the other methods, in which predictor variables are assumed to be fixed.

A conventional Cox proportional hazards model with time-invariant variables and an extended version of Cox hazards model with time-varying variables are both studied in this thesis. This is one of relatively few studies to apply dynamic variables in forecasting financial distress. To the author's knowledge it is the first study to provide forecasts of survival probabilities using the Cox model with dynamic variables.

## 1.4 Summary of Findings

It is found that the hazards models with the use of multiple-period data show a better performance in out-of-sample forecasts than the logit models with static data. This is consistent with the findings from previous empirical studies using US data (for example, Shumway, 2001; Hillegeist et al., 2004). It is also found that when the multiple-period hazards model uses both accounting and market variables, this produces the best out-of-sample predictions.

Attempts to reflect the varying characteristics of firms' financial status through time are made in Chapter 4 and Chapter 5. First, the thesis examines the effects of lagged changes of predictor variables in predicting financial distress. In the empirical comparison of a model with lagged changes in variables and a model containing level variables only, it is found that inclusion of lagged variables leads to better prediction.

Second, time-varying dynamic variables are included in the Cox hazards model. It is found that this dynamic Cox model achieves superior predictive power to the static logit model in the out-of-sample forecasts.

In Chapter 6, a key finding from the use of a non-parametric data transformation is that allowing for a non-linear relation between the failure risk and predictor variables leads to a substantive increase in the predictive power of the model. This result is notable. On the other hand, evidence from the empirical analysis using macroeconomic variables does not support the argument that the inclusion of these variables would reduce unobserved heterogeneity in the baseline hazard

function, thereby enhancing model performance. Variables reflecting the macroeconomic conditions do not contribute additional predictive power in forecasting financial distress.

## **1.5 Structure of the Thesis**

Chapter 2 provides a broad review of the prior literature. It first delineates the empirical approach of early studies in financial distress modelling and describes how models have advanced over time. It also documents the debate over alternative approaches. It introduces the role of time domain in predicting financial distress and motivates the dynamic prediction of corporate failure pursued in this study.

Chapter 3 presents the data and methods used in this thesis, and introduces the Cox proportional hazards model. The chapter introduces the data sample of Australian listed companies covering the period from 1995 to 2006. The sample covers 1,703 non-financial companies. Chapter 3 also suggests model evaluation techniques to measure the model's predictive ability.

In Chapter 4, empirical analysis is carried out to examine three issues. First, given a growing literature on the concern of the discrepancy between multiple-period bankruptcy data and single-period forecasting models, the chapter examines the effectiveness of the use of multiple years of data for all firms when estimating financial distress models. Second, it evaluates the usefulness of the information from accounting ratios and equity prices in measuring the failure risk. Third, the chapter develops a model to capture the historical changes of a firm's financial performance

and examines whether this makes any contribution to improving the predictive power of the model.

Chapter 5 develops a Cox hazards model with dynamic variables to estimate survival probabilities and make dynamic financial distress predictions for Australian listed companies. The approach to solving the problem of estimating the baseline hazard function is described. Also, introduced in this chapter are the SAS programs written for the purpose of model estimation and validation.

Chapter 6 empirically evaluates the model's capacity to predict financial distress of Australian companies when including the impact of macroeconomic variables and allowing for the effect of a non-linear relation between financial distress and the predictor variables.

Chapter 7 summarises the key findings of this thesis and discusses its contributions. The chapter then discusses some limitations of the thesis and provides suggestions for future research directions.

# **CHAPTER 2: REVIEW OF CORPORATE BANKRUPTCY PREDICTION**

## **2.1 Introduction**

This chapter reviews relevant literature in the area of corporate bankruptcy prediction. It provides a brief background to bankruptcy prediction and reviews the development of bankruptcy prediction from its origin to the most contemporary and state-of-the-art models. Particular attention is given to the effect of applying the time dimension to the information contained in firm-specific variables and macroeconomic variables.

## **2.2 Background to Bankruptcy Prediction**

### **2.2.1 Definition of Bankruptcy**

There are various definitions for bankruptcy in the literature. Overall, bankruptcy is defined as a condition in which a business cannot meet its debt obligations and, as a result, the company in question is unable to continue its business. According to Altman (2000), the definition of bankruptcy is “the situation that a company cannot pay lenders, preferred stock, shareholders, suppliers, etc, or a bill is overdrawn, or the company is bankrupt according to the law” (Altman 1968, p.1). An alternative definition (Altman, 2000) is that a firm is bankrupt when its liabilities exceed the value of its assets.

There are also variations in the terminology used in this area of study. Under Australian law the term bankruptcy only applies to individuals. Companies can seek voluntary administration, or creditors can place the company into the hands of a receiver or liquidator. Therefore, some authors prefer to use the term financial distress instead of bankruptcy, and various criteria have been used for the purpose of empirically identifying “bankrupt” firms. In this dissertation, the term financial distress is used, as it studies corporate failures in Australia.

### **2.2.2 The Use of Financial Ratios in Early Financial Distress Prediction**

One of the key components in the study of financial distress prediction is the use of financial ratios as predictor variables. Bankers have long used financial statements to assess the creditworthiness of borrowers. It is no surprise to find, therefore, that financial ratios were among the first variables used in models to predict the bankruptcy of a company. Although there is no single theory of corporate bankruptcy, bankers have usually examined the ratio of current assets to current liabilities as a criterion to grant loans to borrowers.

Most of the early bankruptcy prediction studies before the 1980s aimed to improve prediction accuracy by choosing appropriate financial ratios for the analysis. Among a large number of ratios proposed in the literature (Foster, 1986; Ohlson, 1980; Rose, Andrews and Giroux, 1982; Zopounidis, 1987), the most famous and popular financial ratios are those chosen by Altman (1968). Because of the large number of variables (ratios) found to be significant indicators of corporate problems, Altman compiled a list of 22 potentially helpful variables and classified them into one

of five standard categories, including liquidity, profitability, leverage, solvency, and activity (Altman, 2000).

## **2.3 Reviews of Bankruptcy Prediction Models**

### **2.3.1 Introduction to Bankruptcy Prediction Modelling**

Research on bankruptcy prediction has been of substantial interest to accounting and finance academics and practitioners for the last four decades. Bankruptcy prediction models generally provide measures of financial distress and are routinely used by researchers to evaluate the financial health of companies (Grice and Dugan, 2001).

A number of empirical approaches have been employed in bankruptcy prediction modelling since the pioneering work of financial predictive modelling by Beaver (1966), Altman (1968) and Ohlson (1980). The traditional approach to predicting corporate bankruptcy has been to apply a statistical classification technique to a set of samples containing both bankrupt and non-bankrupt firms. The two most widely used techniques are multivariate discriminant analysis (Altman, 1968) and logit analysis (Ohlson, 1980). Predicting the bankruptcy of a firm requires classification where, given a set of classes (here, bankrupt and non-bankrupt) and a set of input data vectors (financial ratios), the task involved is to assign each input data vector to one of these classes.

Generally, the statistical techniques for corporate bankruptcy prediction consist of three parts (Dimitras, Zanakis and Zopounidis, 1996):

- a) sample selection and collection of data (variables and sample sizes);
- b) selection of method and specific variables (ratios) to develop a predictive model;
- c) model validation, i.e., statistical significance and accuracy of results.

In this section, some notable classical statistical analysis techniques, such as univariate analysis, multivariate discriminant analysis and logistic regression, are introduced, followed by a presentation of the main features of these techniques and their specific advantages and disadvantages. The section then discusses more sophisticated alternative modelling techniques such as neural networks and survival analysis and their corresponding features.

## **2.3.2 Early Bankruptcy Prediction Studies**

### ***2.3.2.1 Univariate Statistical Methods***

Univariate statistical methods were first used to discriminate between healthy and failing companies (Back, Laitinen, Sere and Wezel, 1996). William Beaver (1966), one of the earliest researchers, introduced a univariate approach for the classification of companies into two groups by using some financial ratios. The ratios were used individually and a cut-off score was estimated for each ratio on the basis of minimising misclassifications.

Beaver (1966) stratified financial statement data of companies into years prior to failure and examined the predictive ability of financial ratios. In the univariate statistical approaches to predicting corporate bankruptcy, it is assumed that a single variable can be used for predictive purposes. Beaver concluded that the cash flow to

total debt ratio was the single most important factor to consider in predicting bankruptcy.

However, Beaver's (1966) univariate analysis is deemed to lack practicality. Atiyya (2001) makes the criticism that his analysis is too simple in that it is based on studying one financial ratio at a time and on developing a cut-off threshold for each ratio. Moreover, there is a variety of factors that describe the financial status of a company, so that a single ratio cannot provide sufficient information for complete analysis (Dimitras et al., 1996).

Even though univariate methods received considerable criticism, Beaver's (1966) idea led the way for developing discriminant analysis and it was expanded in subsequent research on corporate bankruptcy.

### ***2.3.2.2 Multivariate Discriminant Analysis***

Beaver's univariate analysis set the stage for a multivariate discriminant analysis to find a bankruptcy prediction model (Drapeau, 2004). Multivariate discriminant analysis (MDA), also known as multiple discriminant analysis, is a statistical method that is designed to classify each observation into one of a priori groups based on the individual characteristics of the observation. It is used primarily to classify and make predictions in problems where the dependent variable appears in a qualitative form, for instance, bankrupt or non-bankrupt (Altman, 2000). Classification is accomplished through development of a multiple discriminant function which is generally a linear combination of independent variables. The discriminant function is derived in such a way as to minimise the possibility of misclassification. In applying MDA, part of the data set is used as an analysis sample

to develop the discriminant function. A cut-off score is derived to determine group classification for each observation and the resultant function is then applied to the remainder of the data set (a holdout sample) for validation. A classification matrix is derived for both the analysis sample and the holdout sample. This matrix (also called the confusion matrix) shows the number of observations that have been both correctly and incorrectly classified. Subsequently, predictive accuracy may be estimated, indicating the percentage of observations correctly classified. As in Altman (1968) predictive accuracy declines substantially as the forecast horizon extends beyond one year.

Altman (1968) first used the classical MDA in his Z-score model as the appropriate statistical technique for the purpose of detecting bankruptcy potential. Altman (1968) selected a sample of 33 bankrupt and 33 non-bankrupt companies from 1946 to 1965, and constructed a five-variable model to separate bankrupt and non-bankrupt companies into two groups. The following variables are used in Altman's Z-score model and these financial ratios have been widely used as inputs for many other models (Altman, 2000; Atiya, 2001; Dimitras, Zanakis and Zopounidis, 1996; Grice and Ingram, 2001; Hillegeist, Keating, Cram and Lundstedt 2004; Odom and Sharda, 1990; Shumway, 2001):

- a) working capital/total assets;
- b) retained earnings/total assets;
- c) earnings before interests and taxes/total assets;
- d) market value of equity/book value of total liabilities; and

e) sales/total assets.

Each variable is explained as follows (Altman, 2000; Atiya, 2001):

a) working capital/total assets;

The working capital/total assets ratio is “a measure of the net liquid assets of the company relative to the total capitalization” (Altman 2000, p.10). Working capital is defined as the amount of current assets minus current liabilities. Liquidity is explicitly considered here. If a company experiences consistent operating losses, its current assets will be diminished in relation to its total assets. It is basically the amount of net current assets that indicates the ability of the company to pay its current debt and take advantage of profitable short-term investments. There are three existing liquidity ratios and this operating liquidity ratio is regarded by Altman as being the most valuable, the other two liquidity ratios being the current ratio and the quick ratio.

b) retained earnings/total assets;

Retained earning is defined as “the account which reports the total amount of reinvested earnings and/or losses of a company over its entire life” (Altman 2000, p.10). It means a company’s accumulative earnings since the company’s foundation. This ratio takes into account the age of a company, where it states a young company will have a lower ratio as it has less accumulated earnings. Thus, it is argued that young companies are discriminated against when using this ratio and their chance of being classified as bankrupt is relatively higher than for older companies.

This ratio also indicates the leverage of a company, given that leverage measures the extent to which liabilities are used to purchase assets. Therefore those

companies with high retained earnings, relative to total assets, have lower finance leverage and thus, less risk of bankruptcy.

c) earnings before interests and taxes/total assets;

This ratio measures “the true productivity of the company’s assets”, without consideration of any tax or leverage factors (Altman 2000, p.11). Since the earning power of a company’s assets can ultimately support the company’s existence, this ratio was regarded as being critically important for corporate bankruptcy. Altman (2000) stated that this ratio would continually outperform other profitability measures, including cash flow.

d) market value of equity/book value of total liabilities;

A company can issue and sell new shares in the market to pay off its obligations. The capacity to do that is indicated by the excess of the market value of equity over total liabilities. This measure shows the amount by which “the company’s assets can decline in value before the liabilities exceed the assets and the company becomes insolvent” (Altman 2000, p. 11).

e) sales/total assets;

This ratio shows the ability of the company’s assets to generate sales. Altman argues that it is one measure of management’s capability to manage competitive conditions, and he ranks this ratio as the second most significant variable contributing to the overall discriminating ability of the model (Altman, 2000). However, Atiya (2001) points out that this ratio is the least effective among the five Altman ratios,

because there is a large variation from industry to industry in asset turnover (sales over total assets).

The multivariate discriminant function proposed is as follows (Altman 1968):

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5, \quad (2-1)$$

where  $X_1$  = working capital/total assets,

$X_2$  = retained earnings/total assets,

$X_3$  = earnings before interest and taxes/total assets,

$X_4$  = market value equity/book value of total liabilities,

$X_5$  = sales/total assets, and

$Z$  = overall index.

Based on the sample, all companies having a Z-score greater than 2.99 fall into the non-bankrupt group while a Z-score of below 1.81 places a company in the bankrupt group. The area between these two values is marked as the 'zone of ignorance' or 'grey area'. A Z-score of 2.675 is identified as being the critical point separating bankrupt and non-bankrupt companies.

Although Altman's Z-score model was developed in 1968 using a small sample of 66 manufacturing companies, it still remains the most widely used method for evaluating the financial health of company. Subsequently, many researchers have applied the MDA technique to their studies in bankruptcy prediction (Altman,

Haldeman and Narayanan, 1977; Blum, 1974; Deakin, 1972; Dimitras et al., 1996; Drapeau, 2004; Karels and Prakash, 1987; Odom and Sharda, 1990).

However, Altman's Z-score model had some drawbacks. According to Grice and Ingram (2001), the small sample of companies and the use of equal group sizes of bankrupt and non-bankrupt companies limits generalisation of the results. The sample grossly overrepresents the incidence of bankruptcy relative to the population. Moreover, MDA is only valid under certain restrictive assumptions. It is required that the independent variables in the sample data should be normally distributed with different means but with equal covariance matrices (Dimitras et al., 1996; Atiya, 2001).

### ***2.3.2.3 Logistic Regression***

Logistic regression (LR) has been another multivariate statistical model widely used in many studies. Studies that utilise logistic analysis include Begley, Ming and Satts (1996), Berger, Ofek and Swary (1996), Dichev (1998), Han, Jennings and Noel (1992) and Zavgren (1985). Stickney (1996) commented that during the 1980s and 1990s, the trend has been to use logit analysis rather than multiple discriminant analysis.

The use of the LR approach for bankruptcy prediction was first proposed by Ohlson in 1980. The logit model is based on the cumulative logistic probability function and its use is appropriate in situations involving binary or ordinal response-dependent variables (for example, bankrupt or non-bankrupt). The output from the model is the probability that a firm is in a bankrupt or non-bankrupt state.

Based on a sample that contained 105 bankrupt and 2,058 non-bankrupt firms Ohlson (1980) estimated the following model:

$$\text{Probability of bankruptcy} = \frac{1}{1 + e^{-y}}, \quad (2-2)$$

Where the following parameter estimates were made:

$$Y = -1.3 - 0.4X_1 + 6.0X_2 - 1.4X_3 + 0.1X_4 - 2.4X_5 - 1.8X_6 + 0.3X_7 - 1.7X_8 - 0.5X_9.$$

The variables were selected on the basis of their popularity in the literature and were:

$X_1 = \log(\text{total assets/GNP price-level index}),$

$X_2 = \text{total liabilities/total assets},$

$X_3 = \text{working capital/total assets},$

$X_4 = \text{current liabilities/current assets},$

$X_5 = \text{one if total liabilities exceed total assets, zero otherwise},$

$X_6 = \text{net income/total assets},$

$X_7 = \text{funds provided by operations/total liabilities},$

$X_8 = \text{one if net income was negative for the last two years, zero otherwise},$

$X_9 = \text{measure of change in net income, and}$

$Y = \text{overall risk index}.$

LR has been claimed to be superior to MDA because it does not require the assumption of normality and equal covariance matrices. However, in terms of predictive accuracy, its use in modelling bankruptcy has not demonstrated dramatic improvements over MDA (Back et al., 1996; Serrano, 1997).

### **2.3.3 Alternative Techniques**

#### ***2.3.3.1 The Advent of Non-parametric Techniques***

Non-parametric techniques surged in the study of financial distress prediction since they alleviate the problem of parametric models, that is, the restrictive assumptions about the underlying probability distribution of the variables. Raghupathi, Schkade and Raju (1991) claim that traditional statistical approaches are of limited use in deriving an appropriate prediction model in the absence of well-defined domain models. Statistical techniques require the assumption of a certain functional form for relating dependent variables to independent variables. When the assumptions regarding the functional form are violated the model is misspecified and significance tests are biased. In this regard, non-parametric approaches, such as recursive partitioning algorithms (Frydman, Altman and Kao, 1985), and neural networks techniques (Odom and Sharda, 1990; Coats and Fant, 1992; Tam and Kiang, 1992; Wilson and Sharda, 1994) can provide a more general framework for determining relationships in the data as they do not require the specification of any functional form. Therefore, the non-parametric nature of pattern recognition methods allows one to bypass the statistical problems of MDA and qualitative response regression models (Frydman et al., 1985).

### ***2.3.3.2 Neural Networks in Bankruptcy Prediction***

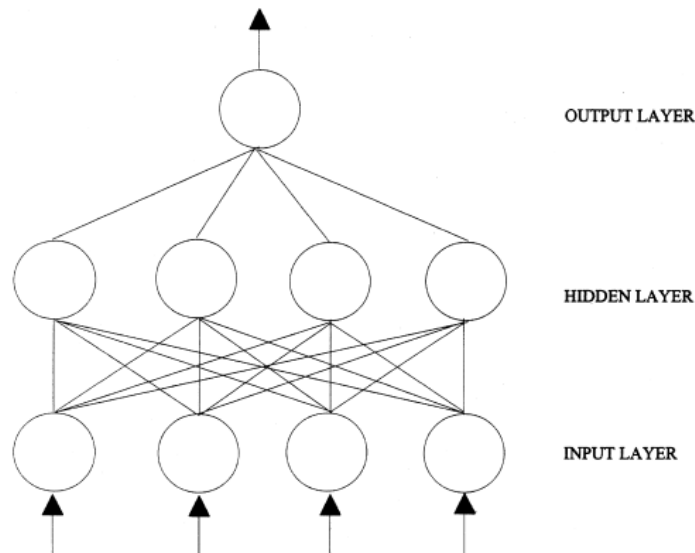
Recent studies in Neural Networks (NNs) show that NNs are suitable for many tasks in pattern recognition and pattern classification (Rudorfer, 1995). NNs have non-linear, non-parametric adaptive-learning properties in modelling and forecasting (Zhang, Hu, Patuwo and Indro, 1999).

In 1990, the NNs technique was introduced into the field of corporate bankruptcy prediction and it has been a popular technique ever since. Odom and Sharda (1990) were the first to apply NNs to bankruptcy prediction. Other studies using the NNs technique are Altman, Marco and Varetto (1994), Atiya (2001), Cadden (1991), Coats and Fant (1992), Tam and Kiang (1992) and Wilson and Sharda (1994).

A neural network is typically composed of several layers of many computing elements called nodes. Each node receives input information from external inputs or from the output signal of other nodes. While processing the signals locally through a transfer function, the node outputs a transformed signal to other nodes (Zhang et al., 1999). A neural network has certain architecture, that is, the number of layers, the number of nodes in each layer and how the nodes are connected (Serrano, 1997).

Most neural network approaches to bankruptcy prediction use a multi-layer perceptron (MLP). In MLP, all nodes and layers are arranged in a feed forward manner (Zhang et al., 1999). The feed forward layered network contains three kinds of layers. The first layer is called the input layer where external information is received. The last layer is called the output layer where the network produces the final solution. In between, there are one or more internal or hidden layers. As the number

of hidden layers increases, the network becomes more complex. An MLP with one hidden layer and several output neurons is shown in Figure 2-1. This three-layer MLP is the most commonly used NNs structure for two-group classification problems like the bankruptcy prediction (Zhang et al.).



**Figure 2-1: A Typical Fully Connected Feed Forward Neural Network (MLP) Used for Two-Group Classification Problems (source from Zhang et al., 1999)**

Odom and Sharda (1990) used Altman's financial ratios as inputs to the NNs, and applied their method to 128 US companies. Most of the data used for the bankrupt companies are from the last financial statement before declaring bankruptcy. Odom and Sharda applied the three-layer feed forward MLP in their study. They compared the study results of NNs to those of MDA. Using different ratios of bankrupt companies to non-bankrupt companies in training samples, Odom and Sharda tested the effects of a different mixture level on the predictive ability of NNs and discriminant analysis. They found that NNs provided a more accurate and robust prediction ability (for example, one result showed that MDA had a correct prediction

rate of 59.26% compared to NNs with a rate of 77.78% for the out-of-sample forecast), regardless of the different sample proportions in training.

Many researchers put emphasis on the superiority of the NNs technique over classical techniques for a number of reasons. First of all, NNs can recognise complex patterns with better accuracy, and they are able to learn from training samples, without any prior knowledge about the underlying problems (Back et al., 1996). Secondly, Coats and Fant (1993) found that non-numeric data can be easily included in an NN because the input data do not need to conform to some linearity assumption. A third advantage is that an NN is perfectly suited for pattern recognition and classification in unstructured environments with noisy data, which may be incomplete, or inconsistent (Hawley, Johnson and Raina, 1990). Hawley et al. add that an NN can overcome the problem of autocorrelation that frequently arises in time series data.

Although the NNs technique seems to deliver strong performance in bankruptcy prediction, it also has some serious shortcomings. It is frequently said that the most important problem related to the use of NNs is the black box problem (Coats and Fant, 1993; Cybinski, 2001; Hawley et al., 1990). The black box problem is that NNs do not reveal the significance of each of the variables and the way they weigh independent variables. So the individual roles that each of the various variables play cannot be determined; thus, it is impossible to understand how the network classifies companies into the bankrupt and non-bankrupt groups. Researchers have no understanding or knowledge concerning how the relations in the layer-structure are estimated. Another major drawback is that NNs can be made to fit the data too well,

thus running the risk of overfitting (Geman, Bienenstock and Dousat, 1992). As a higher number of layers leads to a more complex NN with a higher internal validity, it can cause a higher degree of overfitting and a lower external validity.

## **2.3.4 Models Analysing Longitudinal Data in Corporate Bankruptcy Prediction**

### ***2.3.4.1 Introduction to Survival Analysis***

Survival analysis is a statistical method specifically designed for the study of events, where individuals run through their lifetime and the duration of time until the event of interest occurs is observed. An event can be defined as some qualitative change that occurs at a specific point in time, which exhibits “a relatively sharp disjunction between what precedes and what follows” (Allison 1984, p.9). Once the event of interest is defined, the probability of the event occurring is measured based on possible explanatory variables.

One key feature of survival analysis is that, unlike other statistical methods, it controls for both the occurrence and the timing of events.<sup>2</sup> It has been mainly used in biomedical studies where researchers observe time to death of patients or of laboratory animals. In engineering science, the survival analysis is called failure time analysis as it models the time taken for machines to break down.

Survival analysis is ideally suited for introducing a time dimension into financial distress prediction since it estimates a probability of survival up to time  $t$ . That is, it provides the probability that financial distress will occur at a time  $T$  which

---

<sup>2</sup> Survival analysis is also known as event history analysis, lifetime analysis or duration analysis.

lies beyond the time horizon  $t$ , for a range of values of  $t$ . Thus, a time dimension is embedded in the dependent variable of the model.

The application of survival analysis to financial distress modelling began in the 1980s and grew in use through the 1990s (Lane, Looney and Wansley, 1986; Crapp and Stevenson, 1987; Whalen, 1991; Chen and Lee, 1993; Bandopadhyaya, 1994; Wheelock and Wilson, 1995; Hill, Perry and Andes, 1996; Helwege, 1996; George, Spiceland and George, 1996). Survival analysis is a natural choice for bankruptcy prediction since it allows the estimation of the probability that a firm survives or goes bankrupt at each point in time  $t$  over the forecast period. From 2000 onwards there has been growing use of survival analysis in financial distress modelling (Wheelock and Wilson, 2000; Partington, Russel, Stevenson and Torbey, 2001; Shumway, 2001; Parker, Peters and Turetsky, 2002; Disney, Haskel and Haden, 2003; Chava and Jarrow, 2004; Campbell, Hilscher, and Szilagyi, 2008; Nam, Kim, Park and Lee, 2008; Bonfim, 2009; Cole and Wu, 2009).

While other statistical models analyse an event's probability using variables based on data at one time point, survival analysis is based on data collected across time. Additionally, survival analysis not only calculates the probability of the event but also analyses changes in variables over time and their effect before the event occurs. Hence, survival analysis models are also named duration models, and enable time to be incorporated into failure prediction. The technique can be extended by treating the input data as time-varying variables. By incorporating a time dimension into both the dependent and independent variables, survival analysis has a substantial advantage over other methods in predicting bankruptcy.

#### ***2.3.4.2 Forecast with Multiple-Period Data***

In recent studies of financial distress prediction, the need to bring the time dimension into account is increasingly being recognised. LeClere (2000) analysed comparative performance between qualitative response models and survival analysis. The study points out that qualitative response models, such as logistic regression or probit models, employ data from the time period directly preceding the occurrence of the event of financial distress. Hence, the model is static in that it disregards the company's entire history preceding the event.

Shumway's (2001) pivotal work highlights the need to use multiple firm-year observations for each firm in financial distress prediction. He points out the discordance between single-period bankruptcy prediction models, which have been commonly used, and multiple-period bankruptcy data. He argues that such models yield biased and inconsistent estimates because they do not take into account the fact that firm characteristics change over time. By "exploiting each firm's time-series data using the hazard model with annual observations included as time-varying covariate" (Shumway 2001, p.102), he demonstrates that utilising more data produces more accurate parameter estimates, and thus leads to superior out-of-sample forecasts.

In a similar context, Hillegeist, Keating, Cram and Lundstedt (2004) also suggested that multiple year observations for a firm's financial condition should be included to estimate the model. It was demonstrated that they could obtain more efficient coefficient estimates once all available data were used in their estimation.

Furthermore, Hillegeist et al. (2004) suggested disassembling the predictor variables into lagged levels and changes, in the pursuit of extracting additional

information from historical data, to improve the predictive accuracy of a model. Similarly, Jones and Hensher (2004) used lagged changes of a variable in an attempt to incorporate the accumulating impact of changing financial characteristics over time. Even though these studies did not provide any evidence to support lagged effects, further investigation is required to provide definitive evidence.

#### ***2.3.4.3 Forecast with Time-Varying Variables***

An alternative method for applying the time dimension to independent variables is to make them time-varying. Here, the predictor variables are modified to change in value over the observation period. Thus, for example, a vector of ratios providing a firm's return on assets over a 10-year period would be treated as a single variable, but the value of that variable would be updated as the firm is observed over time in the survival model estimations.

Nam, Kim, Park and Lee (2008) extended Shumway (2001) to develop a discrete-time duration model with time-varying covariates. They examined the effectiveness of time-varying variables, which reflect changes in idiosyncratic firm financial characteristics, in the prediction of corporate bankruptcy in the Korean Stock Exchange (KSE) during the period of the Asian economic crisis in 1998-2000. Their out-of-sample forecasting results showed that the duration model with time-varying covariates provides somewhat better forecasts than a static logit model.

Cole and Wu (2009) also used Shumway's (2001) simple dynamic hazard model with time-varying covariates for US bank failure data. They show that the out-of-sample forecast accuracy of their dynamic hazard model is considerably higher

compared to the simple one-period probit model and concluded that the time-varying bank-specific variables enhance forecasting accuracy.

#### 2.3.4.4 Cox Model with Time-Varying Variables

The pre-eminent model in survival analysis is the Cox proportional hazards model (Cox, 1972) and it is particularly convenient to use in estimating models with time-varying covariates. However, for reasons discussed below, using this model to make forecasts is problematic with time-varying variables.

In the standard proportional hazards model the hazard for each case is a fixed proportion of the hazard of any other observation at any point in time. Therefore the ratio of hazards for any two observations with independent covariates is constant over time. For two companies,  $i$  and  $m$ , the ratio of the hazards can be expressed such that:

$$\frac{h_i(t | z)}{h_m(t | z)} = \frac{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^i\right\}}{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^m\right\}} = \exp\left\{\sum_{j=1}^p \beta_j (z_j^i - z_j^m)\right\} = k, \quad (2-3)$$

where  $h_i(t | z)$  is the hazard rate for firm  $i$  at time  $t$ .  $z$  is a row vector of measured covariates ( $z_j^i$  denotes the value of the  $j$ th covariate for the  $i$ th firm) and  $\beta$  is a column vector of coefficients ( $\beta_j$  is the corresponding coefficient for  $z_j^i$ ). The components of  $h_i(t | z)$  comprise a baseline hazard,  $h_0(t)$  which measures the effect of time on the hazard in the absence of covariates, and an exponential term,  $\exp\left\{\sum_{j=1}^p \beta_j z_j^i\right\}$  which

determines the proportional effect of the risk factors. The baseline hazard is assumed to be identical for all entities in the sample.

The result is that the plots of the hazard function for all observations are parallel, and consequently this property of proportionality can be exploited in estimating the baseline hazard.

On the other hand, with the time-varying variables the proportionality no longer applies. Since:

$$\frac{h_i(t | z(t))}{h_m(t | z(t))} = \frac{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^i(t)\right\}}{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^m(t)\right\}} = \exp\left\{\sum_{j=1}^p \beta_j (z_j^i(t) - z_j^m(t))\right\} \neq k. \quad (2-4)$$

$h_i(t | z(t))$  is the time-varying hazard function for firm  $i$  where the hazard at time  $t$  depends on the value of measured covariates at time  $t$ .  $z_j^i(t)$  denotes the value of the  $j$ th covariate at time  $t$  for the  $i$ th firm, and  $\beta_j$  is the corresponding coefficient for  $z_j^i$ .

The outcome is that there is substantial difficulty in estimating the baseline hazard and consequently in forming forecasts. Previous studies (for example, Wheelock and Wilson, 1995; Kim, Anderson, Amburgey and Hickman, 1995) have not reported the baseline hazard estimates since estimates of the baseline hazard are difficult to obtain when covariates in the model are time-varying. Recent advances, however, have made this somewhat less problematic. Chen, Yen, Wu, Liao, Liou, Kuo, and Chen (2005) estimated a time-dependent (time-varying) Cox hazards model

for patients' deaths due to liver cancer. Using a method from Anderson (1992), they estimated the integrated baseline hazard and forecast survival probabilities for each patient.

## **2.4 Empirical Approaches to Predicting Corporate Failure at the Firm Level and the Macroeconomic Level**

### **2.4.1 Accounting-Ratio-Based Models versus Market-Based Models**

This section focuses on financial distress studies which have been conducted at the firm level. In particular, it examines the usefulness of market data in predicting financial distress. It also reviews empirical comparisons of models using accounting and stock market information.

At the outset, it should be noted that the term market-based financial distress model can mean two things: first, the use of stock market data using a statistical model of distress prediction, such as a logit model; second, distress prediction based on option pricing.<sup>3</sup>

In contrast to models using market data, models based on accounting data are found to have the following limitations. Firstly, Hillegeist et al. (2004) postulated that accounting-ratio analysis is backward-looking, while financial distress prediction is ideally conducted in a forward-looking manner. Given that the probability of default

---

<sup>3</sup> The statistical approach has been the traditional financial distress prediction method. The option pricing approach is also known as a structural approach, or a contingent claims valuation approach. It is based on the framework of Merton's option pricing model (1974) to measure the probability of default. This approach is best known through a commercial product, Moody's KMV model. In comparisons between the traditional statistical approach and the structural approach, prior literature tends to use the term market-based model for the latter and accounting-ratio-based model for the former.

should indicate the likelihood of the future status of the firm, the information from these financial statements is deemed less effective in producing an accurate and reliable forecast (Vassalou and Xing, 2004).

Secondly, due to the conservatism principle, book values of firm assets are often understated compared to their market values, which may lead to overstatement of accounting-based leverage figures. This may limit the performance of any accounting-based measure of bankruptcy probability (Hillegeist et al., 2004).

Thirdly, although the volatility of the firm's assets is considered one of the key variables in predicting default probability, it is not reported in financial statements (Hillegeist et al., 2004; Vassalou and Xing, 2004). In the case where two firms have identical leverage ratios, their probability of default can be significantly different based on their asset volatilities (Vassalou and Xing, 2004). Volatility provides additional information on the likelihood of the firm's assets falling below the firm's capacity to meet its debt obligations. Therefore, the absence of a volatility measure in the accounting-based models may limit their performance in financial distress forecasting.

In addition, a fourth limitation is that the data used in accounting-based models are often incomplete, especially for financially distressed firms. This is due to the cessation of regular financial reports when firms begin to become financially distressed. Hence, these firms will be excluded from models requiring complete data sets. Conversely, equity market data are available as long as a firm continues trading.

Furthermore, Agarwal and Taffler (2008) claimed that another limitation of accounting-based models is their ad-hoc sample-specific nature, which causes them to

be inconsistent with data sets other than the estimation sample. This criticism was echoed by Gharghori, Chan and Faff (2006). In contrast, since market-based models can be computed for any publicly traded firm using a theoretically derived formula, they can be generalised.

Empirical evidence has also been provided in favour of market-based models. Shumway (2001) found that about half of the accounting ratios that have been used in previous literature are not statistically significant. Moreover, Beaver, McNichols and Rhie (2005) supported Shumway (2001) by demonstrating that adding market-based variables into the hazard model enhanced the predictive power relative to the model with accounting ratios only. Hillegeist et al. (2004) showed their model carried more information about failure than poorly performing accounting-ratio-based models. Chava and Jarrow (2004) also found that accounting variables add little predictive power when market variables were already included in the bankruptcy model.

Some researchers have invoked the efficient market hypothesis, that is, market prices contain all the information in accounting reports, including the prospect of financial distress. However, Sloan (1996) suggested that the market does not efficiently incorporate all the information in the accounting reports, whereas Chava and Jarrow (2004) demonstrated that market variables reflect all publicly available information regarding bankruptcy, which is contained in accounting reports. They showed that the market-based model significantly outperformed the accounting-based model in terms of predictive power, which can arguably be attributed to the timely information provided by stock price variables. This was demonstrated back in 1968 by Ball and Brown. They argued that the accounting data are value-relevant but is not

timely and demonstrated that most of the earnings information, although not all of it, is reflected in the price before the earnings announcements are made.

Notwithstanding that a number of studies have demonstrated that the market-based models outperform the accounting-ratio models as a measure of default risk (Shumway, 2001; Hillegeist et al., 2004; Chava and Jarrow, 2004; Beaver et al., 2005; Gharghori et al., 2006), accounting-ratio-based models are still widely used and supported by other studies (Brockman and Turtle, 2003; Reisz and Perlich, 2007; Agarwal and Taffler, 2008; Bharath and Shumway, 2008; Campbell, Hilscher, and Szilagyi, 2008; Fargher and Kalotay, 2009). Therefore it is necessary to consider the benefits of the accounting-based models as presented in those studies.

Firstly, for unlisted firms there is little choice but to use accounting-ratio analysis. Secondly, some studies have shown the superior performance of accounting-based statistical models compared to option pricing models. Agarwal and Taffler (2008) in their UK study compared two different approaches, the statistical z-score model (accounting-ratio-based model) of Taffler (1984) and the Moody's KMV option-based model and concluded that traditional accounting-ratio-based models have similar, or even better, predictive power compared to the market-based model. Similarly, Reisz and Perlich (2007) found that Altman's (1968) z-score performs slightly better in failure prediction over a one-year period than both their KMV-type and their computationally more intensive down-and-out call option models (barrier option models).

In summary, the literature does not universally support one model over the other, thus, it is still an open question. Therefore, it is worthwhile to provide empirical

evidence, using Australian data, on whether a market-based estimation of the probability of financial distress performs better relative to an accounting-based measure.

#### **2.4.2 Macroeconomic Factors in Financial Distress Prediction**

Thus far the significance of firm-specific variables (internal factors) in financial distress modelling has been discussed but now the influence of macroeconomic external factors in prediction models will be addressed. In the literature, relatively little attention has been paid to this issue, especially in relation to evaluating the predictive accuracy of the firm's future financial condition.

Recently, some researchers have proposed including 'broader measures of the economic environment' (Partington et al., 2001) in order to help properly model the external environment of the firm (Cybinski, 2001; Grice and Dugan, 2001; Liu, 2004; Shumway, 2001). General economic conditions may have a direct impact on the activities of individual firms. As Rose et al. (1982) point out, failure is more likely to occur in an economic downturn. Therefore money and capital market conditions are significant factors in the financial stability of a firm.

Similarly, Kane, Richardson and Graybeal (1996) and Richardson, Kane and Lobingier (1998) also considered the effect of economic recession on corporate failure and found that failure prediction models, which control the effects of economic recession information, have better explanatory and predictive power. In a related work, Rösch and Sheule (2005) examined default and recovery rates. They found that compared to models without business cycle indicators, models that include

macroeconomic risks better explain cyclical fluctuations in default rates and hence reduce uncertainty in regard to the forecast of loss given default.

Furthermore, Liu (2004) investigated the causes of corporate failures at the macroeconomic level by examining both a short-run and long-run relationship between corporate failures and the performance of the macroeconomy in the UK. Liu (2004) strongly asserted that company liquidations or failures can be significantly influenced by the general macroeconomic conditions, and demonstrated that interest rates, real profits, real credit, price and the corporate birth rate significantly affected company failure rates over the period between 1966 and 1999.

More recently, Nam, Kim, Park and Lee (2008) examined the effectiveness of a bankruptcy forecasting model (a discrete-time duration model) with macroeconomic risk factors included. They used volatility of foreign exchange rates and interest rates as proxies for macroeconomic changes. They demonstrated that the macro-dependent duration model showed better prediction ability, compared to the forecasting performance of a model without macroeconomic variables. In particular they put emphasis on the effectiveness of including macroeconomic variables in the failure prediction, especially in the situation where dramatic economic changes occur.

Bellotti and Crook (2009) examined whether the probability of default in credit card accounts in UK banks may be affected by general economic conditions over time. While comparing the results of survival models with those of standard logistic regression models, they demonstrated that the inclusion of macroeconomic indicators into the base model provides statistically significant improvements in model fit. It also improves the predictive performance of the model. Finally, Bonfim

(2009) studied how idiosyncratic firm characteristics as well as systematic risk factors drive the corporate default process. Bonfim found that the risk of corporate default increases during periods of strong economic growth as banks apply more lenient credit standards. Moreover, the high default rates during economic downturn are only a manifestation of the accumulated risk during economic expansions. The author concluded that both the firms' financial performance and the macroeconomic dynamics explain why firms default.

Nevertheless, the importance of macroeconomic variables for financial distress prediction is not without challenge. Both Li (1999) and Sharma (2001) indicated that market-wide information does not affect the prediction of financial distress. The empirical result of Partington et al. (2001) is that the addition of macroeconomic variables into their bankruptcy payoff model did not provide incremental predictive performance compared to a model containing only firm-specific variables. Cole and Wu (2009) also found no significant effects from macroeconomic variables themselves, but only significant interactions even though the macro-interactions did not improve forecast accuracy.

## **2.5 Non-Linear Approach to Corporate Failure Prediction**

While most benchmark models in financial distress prediction relate the risk of firm failure with the variables in a linear approach, little attention has been paid to this issue in prior literature. However, recent studies have shown some interest in using a non-linear approach in developing more accurate prediction models. Loffler and Posch (2007) pointed out it is probable that there is a non-linear relation between

predictor variables and the default probabilities. They demonstrated that the model's fit had greatly improved after the variables were remodelled with logit transformations. Further, in Chan, Faff, Gharghori, and Lajbcygier (2008), non-linearities between accounting variables and default risk were examined with new non-linear models, known as logistic generalised additive models. This result validates the superiority of non-linear models' forecasting performance over their linear counterparts. This prospect of increased predictive power of non-linear modelling in financial distress prediction motivates this study to further investigate the non-linear approach to failure prediction.

## **2.6 Measuring Model Accuracy – Problems and Resolutions**

### **2.6.1 Problems of State Forecasts**

One of the problems stated in the literature is the issue of how to assess the predictive accuracy of a model. When a model is trying to predict something with binary or categorical values – for example, in this study predicting whether a company should be classified into a survivor or failure group – there is a problem resulting in the assessment of predictive accuracy. This is because the model normally produces continuous values (e.g., survival probability), not categorical values (state). Thus, when using a model for forecasting states, the output needs to be calibrated to determine what ranges correspond to which categories.

However, if a state forecast is made then tests of forecast accuracy will be a joint test, where the accuracy of the probability will be tested in combination with the accuracy of the rule used to convert the probability to a state. In relation to the current

study, two questions arise in this process. First, at which point  $t$  in the time profile should the probabilities be observed? Second, what will be the optimal cut-off probability value to discriminate between the two groups of those with failing and those with surviving forecasts? These are difficult issues to address.

Pacey and Pham (1990) were of the opinion that assessment of the accuracy of financial distress models is often misleading because of (i) the use of arbitrary cut-off points and (ii) the assumption of equal costs of errors in prediction tests. The appropriate corrective measures would be as follows: (i) derive the optimal cut-off point based on minimising the costs of misclassification; and (ii) explicitly define the cost of Type I and Type II errors.

Optimising the cut-off probability requires a clear understanding of the likely total cost of Type I and Type II errors in the specific decision-making context (Partington et al., 2001). Given the greater seriousness of Type I errors, it is assumed that the misclassification cost for Type I errors is far higher than that of Type II errors (Altman et al., 1977).<sup>4</sup> Based on this assumption, some researchers have attempted to draw an optimal cut-off point where it yields the lowest Type I error (Koh, 1992). The problem with this is that there is a far higher incidence of healthy firms than failing ones. Thus even a small rate of Type II errors may involve a large number of firms. Consequently, as Pacey and Pham (1990) portrayed, even a small rate of Type II errors with a small cost per error scales to a large cost overall. It becomes so large that it may render the forecasts worthless.

---

<sup>4</sup> Altman et al. (1977) has proven that Type I error rates could be 35 times more costly than Type II error rates in bankruptcy prediction.

### **2.6.2 Possible Remedies**

The fundamental question here will be how to measure the accuracy of the probability forecast. There are techniques to do this, which the bankruptcy literature has given limited attention.

A question that immediately arises is how to measure the relative costs of misclassification for Type I errors and Type II errors. This is one of the most challenging unsolved issues in extant studies. Koh (1992) pointed out that it is impractical to measure the misclassification cost of Type I and Type II errors in association with bankruptcy prediction. This is because the costs of loss from incorrect predictions are difficult to quantify. The costs to assess are loss given default, lost profit and lost goodwill from refusing to make a loan. Not only are these costs difficult to quantify with precision, they are likely to vary from loan to loan. However, it may be possible to derive stochastic-dominance-like criteria that allow choice between models in the absence of exact measurements of Type I and Type II error costs. Receiver operating characteristics (ROC) curves provide one example of this. Provided the ROC curves do not intersect, the model giving the highest ROC curve in the upper left quadrant dominates the other models. It dominates in the sense that it has a better hit rate and lower false alarm rate than any of the other models, at all possible cut-off probabilities used to classify the firm as likely to fail or not.

## **2.7 Conclusion**

This chapter reviews the historical studies of financial distress modelling and its advances with discussion on alternative methods. Altman's multivariate

discriminative analysis (1968) and Ohlson's logit analysis (1980) have been considered as benchmarks of financial distress study since their first advent, and they are still being widely used. But such parametric approaches are found to possess weaknesses in regard to the validity and effectiveness of the classical statistical methods, being largely reliant on some restrictive assumptions, such as linearity, normality and independence among predictor variables. Therefore, the trend for non-parametric neural networks in the 1990s was developed in order to be free from these constraints in financial distress prediction. Nevertheless, they could not escape criticism for the so-called black box problem. In search of a trade-off between the two, a semi-parametric model has been proposed in this study, in particular, the Cox proportional hazards model. Chapter 3 will elaborate on this method.

Furthermore, this chapter provides extant literature that has examined the influencing factors on financial distress prediction, including historical data, market data, time dimension, the economy, and non-linearity. It is apparent from the literature review provided in this chapter that the contradictory evidence found in previous literature, particularly the scarcity of literature on the use of lagged changes and non-linear modelling, motivates this study to further examine these issues empirically.

Chapter 4 provides empirical evidence on three research issues discussed in Section 2.3.4.2 and 2.4.1. It examines any improvement in prediction ability from the use of multiple-period data, the addition of market-based information and the inclusion of lagged changes in variables. Chapter 5 challenges the problem of estimating a baseline hazard when a Cox model uses time-varying variables, profiled in Section 2.3.4.4. It provides the method to overcome the technical difficulties in

previous literature and hence offers a prospect of dynamic prediction of corporate failure with time-varying covariates. Finally, Chapter 6 examines the impact of inclusion of macroeconomic variables on predictive power of a financial distress model. Prior literature that evaluated the forecasting performance of macro-dependent models, addressed in Section 2.4.2, does not provide conclusive evidence on this issue. This chapter also examines whether allowing for a non-linear relation between predictor variables and the risk of financial distress improves forecasts, which is highlighted in Section 2.5.1.

## CHAPTER 3: DATA AND METHODS

### 3.1 Introduction

The purpose of this chapter is to present the data and models employed in this thesis. The chapter firstly specifies the fundamentals of a particular form of survival analysis used in the thesis. The base model is introduced and the estimation method is discussed. This is followed by a description of the data and covariates. This chapter also introduces the evaluation approaches used to measure the predictive accuracy of the models.

### 3.2 Model Construction

#### 3.2.1 Cox Proportional Hazards Model

The key to understanding the Cox model is the concept of the hazard rate, sometimes just called the hazard. The hazard is simply the rate of change of probability over an interval conditional on survival until the start of the interval. The formal definition of the hazard is:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}, \quad (3-1)$$

where  $T$  is the duration of time up until a firm's failure and is also called *time to failure*.  $h(t)$  specifies the instantaneous rate of failure at time  $T = t$  given the firm survives up to time  $t$ .

For an individual firm, *time to failure* is modelled using a proportional hazards framework which is also known as the Cox regression or Cox proportional hazards model as it was proposed by Cox (1972). The Cox proportional hazards model assumes the hazard relationship:

$$h_i(t) = h_0(t) \cdot \exp \left\{ \sum_{j=1}^p \beta_j z_j^i \right\}, \quad (3-2)$$

where  $z$  is a row vector of measured covariates ( $z_j^i$  denotes the value of the  $j$ th covariate for the  $i$ th firm) and  $\beta$  is a column vector of parameters with the appropriate dimensions ( $\beta_j$  is the corresponding coefficient for  $z_j^i$ ).  $h_i(t)$  is the hazard for firm  $i$  at time  $t$ . The components of  $h_i(t)$  consist of a baseline hazard,  $h_0(t)$ , which measures the effect of time on the hazard in the absence of covariates, and an exponential term,  $\exp \left\{ \sum_{j=1}^p \beta_j z_j^i \right\}$ , which determines the proportional effect of the risk factors. The baseline hazard is assumed to be identical for all entities in the sample. An overall measure of a firm's risk of failure is then determined by both the multiplicative interaction of the risk factors (a set of covariates) and the underlying time-related hazard (risk of failure).<sup>5</sup>

This model is known as the semi-parametric method, where specification of the functional form is only required in part of the risk of failure estimation. In equation 3-2 the parametric function is the exponential term where it is specified with a defined functional form. Conversely, the non-parametric function of the equation

---

<sup>5</sup> The model states that the hazard rate for any firm is the product of an arbitrary unspecified baseline hazard rate and an exponentiated set of covariates (LeClere, 2000).

lies in the baseline hazard, which does not require the probability distribution of *time to failure* ( $T$ ) to be specified with a functional form (Partington, Russel, Stevenson, and Torbey, 2001).<sup>6</sup>

The combined input of the effect of the risk factors (covariates) along with the shifting baseline hazard produces changes in the probability of survival over time. Given the hazard rate, it is possible to generate survival probabilities for each firm. The survival function  $S(t)$  defines the probability ( $P$ ) that the event time when the firm experiences failure ( $T$ ) is greater than time  $t$ :

$$S(t) = P(T > t). \quad (3-3)$$

In other words, the survival function specifies the probability that the firm will survive up until time  $t$ . The complementary function of  $S(t)$  is the cumulative distribution function, which is defined as:

$$F(t) = P(T \leq t) = \int_0^t f(x)dx = 1 - S(t). \quad (3-4)$$

It represents the probability that the firm experiences the event before some time  $t$ .

The probability density function  $f(t)$  is the unconditional and instantaneous probability that the event occurs in the period of time from  $t$  to  $t + \Delta t$ :

$$f(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t)}{\Delta t} = -\frac{dS(t)}{dt}. \quad (3-5)$$

---

<sup>6</sup> The lack of specificity of a baseline hazard function makes the model semi-parametric or distribution-free (LeClere, 2000).

The hazard rate is related to the density function and the cumulative probability of failure by the relation in equation 3-6.

$$h(t) = \frac{f(t)}{1 - F(t)}. \quad (3-6)$$

The hazard function,  $h_i(t)$ , and the survival function are related. Once the hazard function has been estimated, then the survival function can be readily derived as follows:

$$S(t) = \exp\left[-\int_0^t h(u) du\right], \quad (3-7)$$

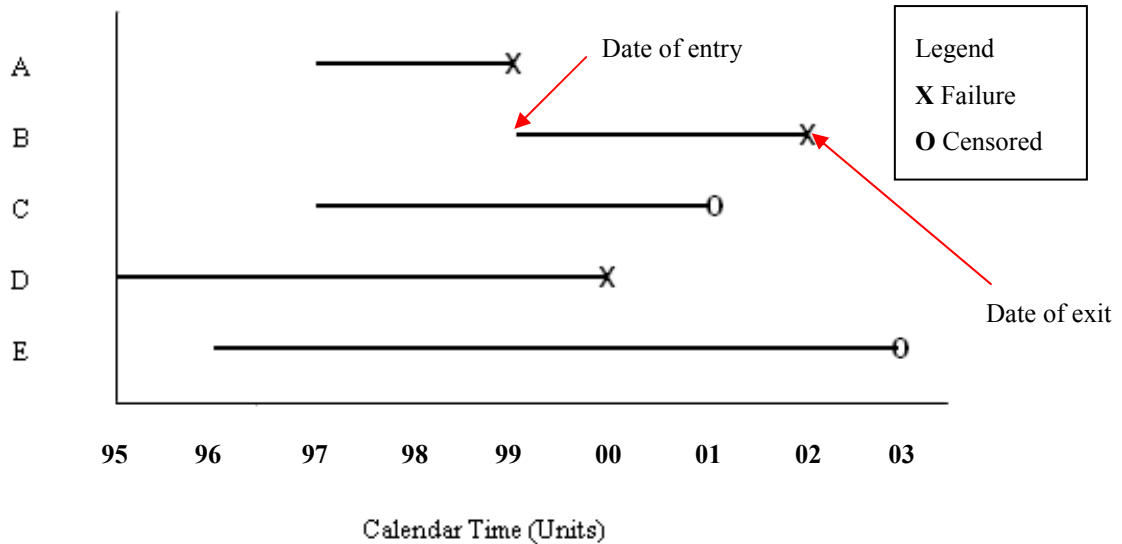
$$h(t) = \frac{f(t)}{S(t)}. \quad (3-8)$$

### 3.2.2 Partial Likelihood Function

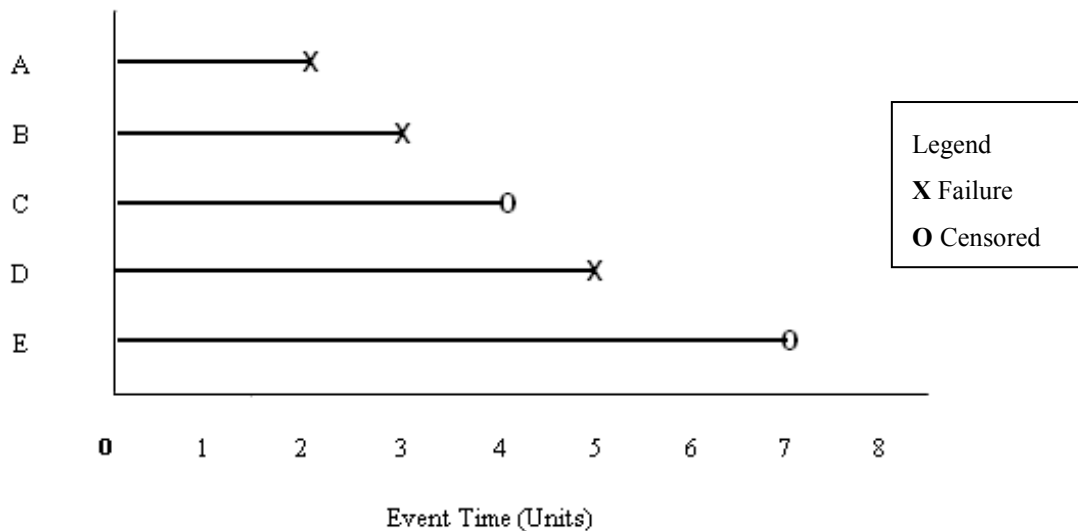
It is helpful to introduce some concepts in survival analysis in order to understand the estimation of the model. First, the risk set  $R(t)$  is defined as the set of firms (individuals) that are observed for risk of event at time  $t$ . Firms are said to enter the risk set when they become at risk of experiencing the event and leave the risk set either when they are censored or when the event occurs (fail or become financially distressed). Being censored means that a firm leaves the risk set for some reasons other than experiencing the event, for example the firm may have been taken over or still be surviving at the termination of the study.

Second, it is important to distinguish between calendar time and event time. A graphical demonstration of the difference between calendar time and event time is presented in Figure 3-1. An event time approach looks to the duration (time spent in the risk set) of a firm and sorts observations according to their duration of study. The event time approach is used in this study, as is commonly the case in other survival analysis studies.

**Panel A: Arrangement of Firms in the Risk Set according to Calendar Time**



**Panel B: Arrangement of Firms in the Risk Set according to Event Time**



**Figure 3-1: Calendar Time versus Event Time**

This Figure presents a graphical demonstration of the difference between arranging the data in terms of “calendar time” and “event time”. Panel A illustrates observations of A to E arranged in calendar time while Panel B does so in event time. It is noted that observations can enter the study at different times in Panel A; however, every observation enters the study at event time 0 in Panel B. The length of the line indicates the lifetime of the observation. An “X” at the end of the line denotes the event of failure, whereas an “O” indicates that the observation has been censored for reasons other than failure.

After constructing the risk set at each event time it is possible to estimate the likelihood of a firm's failure. The probability that firm  $i$  fails, provided that it had survived up until time  $t$ , is calculated by the ratio of the hazard rate of firm  $i$  to the sum of the hazard rates of all firms in the risk set for each time  $t$  as in equation 3-9. Since the hazard is conditional on a vector of covariates  $z$ , henceforth the notation  $h(t|z)$  is used rather than  $h(t)$ .

$$L_i = \frac{h_i(t|z)}{\sum_{k \in R_i(t)} h_k(t|z)} = \frac{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^i\right\}}{\sum_{k \in R_i(t)} h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^k\right\}} = \frac{\exp\left\{\sum_{j=1}^p \beta_j z_j^i\right\}}{\sum_{k \in R_i(t)} \exp\left\{\sum_{j=1}^p \beta_j z_j^k\right\}}. \quad (3-9)$$

The baseline hazard is cancelled out of the numerator and denominator, so the exact times of each failure are irrelevant and only the order of events is required.<sup>7</sup>

Given  $L_i$ , the partial likelihood function can then be obtained by taking the product of the probabilities across all observed failures,  $m$ , such that:

$$PL = \prod_{i=1}^m L_i = \prod_{i=1}^m \left[ \frac{\exp\left\{\sum_{j=1}^p \beta_j z_j^i\right\}}{\sum_{k \in R_i(t)} \exp\left\{\sum_{j=1}^p \beta_j z_j^k\right\}} \right], \quad (3-10)$$

where  $i$  is the firm in the event of failure and  $k$  is the firm in the risk set at time  $t$ .

---

<sup>7</sup> The estimation procedure has to be modified where more than one event occurs at the same time. In the present study, the Efron method of handling tied data is used. The default method is Breslow, which is an appropriate method when ties are relatively few. But this study does not have many tied events at each time point, so Efron or exact method should be used. In this study Efron is used, which is more computationally efficient but provides similar results.

## 3.3 Data

### 3.3.1 Sample Selection

The study sample includes publicly listed companies on the Australian Securities Exchange (ASX) from 1995 to 2006. Firms which are in the financial sector, as indicated by their Global Industry Classification Standard (GICS)<sup>8</sup> code, are excluded from the sample. Annual accounting data are obtained from FinAnalysis (Aspect Financial) and annual market capitalisation data are provided by Securities Industry Research Centre of Asia-Pacific (SIRCA) and Datastream.

Two data filters are applied to the preliminary dataset. First, a complete set of accounting and market capitalisation must be available for every firm; and secondly, information on the firm's failure event must be available. In order to classify firms into groups of non-failed and failed firms, this study follows the approach of Jones and Hensher (2004) and Chan, Faff, Gharghori, and Lajbceygier (2008). Firms are classified as failed if (i) they were delisted due to failure to pay their annual listing fees to the ASX<sup>9</sup>, or (ii) there was an appointment of liquidators, insolvency administrators, or receivers.<sup>10</sup> Companies' failure events in the sample and the dates

---

<sup>8</sup> "GICS is designed as "an enhanced industry classification system jointly developed by Standard & Poor's and Morgan Stanley Capital International (MSCI)" to "meet the needs of the investment community for a classification system that reflects a company's financial performance and financial analysis" (Standard and Poors, 2002: p.4).

<sup>9</sup> According to the Australian Securities Exchange Listing Rule 16.5, a firm can be removed from the official list if the firm does not pay an annual listing fee (ASX 2008, Chapter 17).

<sup>10</sup> According to Australian Corporations Act (2001), three principal forms of bankruptcy proceeding are available under the legislative provisions: (i) voluntary administration (first introduced in Australia in June 1993 under the Corporate Law Reform Act [1992]), (ii) liquidation, and (iii) receivership. Voluntary administration has similarities with Chapter 11 provisions in the US, where the company is effectively given a period of time or "breathing space" to reorganise and/or reconstruct. Under Australian voluntary administration laws, once appointed, the insolvency administrator has a limited period (28 days) to assess the company and recommend to the creditors whether the company should be wound up or enter into a deed of arrangement (this is a contract that binds the company and creditors

of their release to the market in Australia are cross-checked against a number of sources: the ASX's Signal G<sup>11</sup> (Company Announcement data obtained from SIRCA), the deListed Company Database<sup>12</sup>, Nothman (1993) and Chan et al. (2008). Resulting from this, 1,703 non-financial firms are identified with available accounting and market capitalisation data, which comprises 1,570 non-failed firms and 133 failed firms in the final sample.

It is noted that company failure happens on specific dates, but there may be varying periods of lag between the failure event and the onset of financial distress. In the absence of the data to model these lags, the advantage of dynamic probability forecasts, giving a trajectory to failure, lies in the potential of providing early warning signs as the trajectory changes.

Additionally, annual accounting and market capitalisation data are collected for each company. Initially, yearly observations of firms' financial performance from 1989 through 2006 were considered. However, the requirement of complete data and availability of the date of failure results in no failure events in study samples between 1989 and 1993 and only one failure event in 1994. Moreover, the sample sizes are

---

and includes such issues as the order by which creditor claims are to be settled from sale of assets). If the deed of arrangement stage is not reached, then the legislation provides for an automatic transition to liquidation. With respect to (ii) liquidation, there are essentially two types of winding-up procedure available: a creditors' voluntary winding up (decided by special resolution of the company) and a court winding up. In the case of (iii) receiverships, the Corporations Act (2001) provides that a secured creditor, in the event of a firm's insolvency, can appoint a receiver (or a receiver and manager) to recover outstanding claims against the company (extracted from Jones and Hensher (2004, p.1020)).

<sup>11</sup> The company announcements are available via a 'Signal G' service. They detail announcements lodged with the ASX pursuant to the ASX Listing Rules.

<sup>12</sup> deListed is a division of BRG Pacific Pty Limited, holder of Australian Finance Services. deListed provides information on failed companies, including companies suspended from ASX, NZX, NSX and BSX, all historical name changes and delistings for these exchanges, and carries administrators/liquidator/receivers declarations for Australian companies (delisted, 2006).

very small for 1989 to 1991<sup>13</sup>. The data on firms failing in this period may have been deleted from our data sources and, if so, this is likely to raise a problem of survivorship bias. Therefore, the observations between 1989 and 1994 are excluded from the study. It is noted that defaults are small in number in some of the subsequent years such as 1995, 1996 and 1998; however, extensive data checking suggests that survivorship bias (deletion of failed firms from databases) is not an issue in these later periods.

Table 3-1 shows the number of failed and non-failed firms for each year over the sample period of 1995 to 2006. There are several extreme values among the variables observed. Following the approach of Shumway (2001), all values lower than the first percentile of each variable are set to that value, and analogous treatment is applied to all observations higher than the 99th percentile of each variable. The data, after truncation, are described in detail in Section 3.3.4.

The entire sample period (from 1995 to 2006) is divided into two separate samples; an estimation sample (from 1995 to 2002) and a holdout sample (from 2003 to 2006) for tests of predictive accuracy. There is found to be 87 failure events in the estimation sample period and 46 in the holdout.

---

<sup>13</sup> It is expected to have a number of failed observations in these time periods as there was an economy crash in Australia in the early 90s. Nevertheless, our data sources rarely show the failure cases in these periods, though Chan et al. (2008) can identify numerous defaulted firms through their hand-collected dataset.

**Table 3-1: Data Sample**

This table shows the total number of firm-year observations in our study sample, the number of non-failed firm-year observations and the number of failed firm-year observations and the percentages of failed to total firm-year observations for every year over the sample period of 1995 to 2006. The study sample includes financially distressed (failed) firm data from publicly traded companies on the Australian Securities Exchange (ASX) between 1995 and 2006. In the study sample, there are 13,387 firm-year observations in total where 133 failed observations are found.

Year	No. of firm-year observations	No. of non-failed firm-year observations	No. of failed firm-year observations	Percentage of Failed to total firm-year observations
1995	674	671	3	0.45%
1996	728	723	5	0.69%
1997	773	762	11	1.42%
1998	806	799	7	0.87%
1999	873	862	11	1.26%
2000	983	968	15	1.53%
2001	1,043	1,025	18	1.73%
2002	1,054	1,037	17	1.61%
2003	1,061	1,051	10	0.94%
2004	1,128	1,115	13	1.15%
2005	1,210	1,194	16	1.32%
2006	1,240	1,233	7	0.56%

### **3.3.2 Dependent Variables**

The only dependent variable for a traditional bankruptcy prediction model such as a MDA or a logit model is the occurrence of an event of interest. Unlike traditional dichotomous dependent variable models, survival analysis deals with not only the occurrence of the event but also the timing of events, including the duration until the event occurs.

In this study, the event of interest indicates whether the firm evolves to the state of failure, that is, being financially distressed, and the duration represents the period of time between the firm's entry into the risk set and the occurrence of the firm's failure. Companies that experience the event of interest are called observations, while other companies which are yet to fail (or experience the event of interest) are called censored cases. Specifically, companies are considered to be censored if the firm leaves the risk set due to some reason other than failure, such as takeovers or mergers. Accordingly, an event (failure or bankruptcy) indicator is used to distinguish the censored cases from observations. The indicator equals one if a firm becomes financially distressed, otherwise it equals zero.

### **3.3.3 Firm-Specific Variables**

Key predictors for financial distress with firm-specific variables have been identified from previous bankruptcy studies. Variables are selected from the recent major studies by Sobehart and Stein (2000), Shumway (2001), and Campbell, Hilscher, and Szilagyi (2008). As this study is conducted based on Australian data, some variables that were found to have been useful in other Australian studies are also

included (from Castagna and Matolsky, 1981; Jones and Hensher, 2004; Gharghori, Chan and Faff, 2006).

A set of fundamental accounting-based and market-based variables chosen from the aforementioned studies is shown in Table 3-2.

The accounting-based variables include measures of profitability (Net Income/Total Assets (NI/TA)), operating liquidity (Working Capital/Total Assets (WC/TA)), book leverage (Total Liabilities/Total Assets (TL/TA)) and cash flow generating ability (Net Cash Flow from Operations/Total Assets (CF/TA)). As a group, these ratios capture the strength of the firm's financial position. Operating liquidity (WC/TA) has been chosen over an alternative variable, that is, current ratio (CA/CL), because CA/CL in our sample is found to have a great amount of noisy data. Therefore, the current ratio has been excluded to prevent statistical results being heavily influenced by extreme outliers of that ratio.

**Table 3-2: Firm-Specific Predictor Variables Used in Previous Financial Distress Studies**

This table shows predictor variables used in a number of previous bankruptcy studies in the USA and Australia. Variables are selected from the recent major studies by Sobehart and Stein (2000), Shumway (2001), and Campbell, Hilscher, and Szilagyi (2008). As this study is being conducted using Australian data, some of the variables found to be useful in Australian studies are also included (from Castagna and Matolscy, 1981; Jones and Hensher, 2004; Gharghori, Chan and Faff, 2006). Nine predictor variables are initially considered, measuring profitability, leverage (book and market), liquidity, cash flow generating ability, size and growth opportunity, excess return and market sensitivity. The last two market variables are excluded in our model as there are insufficient data on failed observations.

Description	Ratio / Variable	Abbreviation	Source	Frequency	Included in the present study
<b>Accounting-based Variables</b>					
Return on Assets (Profitability)	Net Income / Total Assets	NI / TA	Sobehart and Stein (2000) Shumway (2001)	Annual	Yes
Operating Liquidity	Working Capital / Total Assets	WC / TA	Castagna and Matolscy (1981) Sobehart and Stein(2000) Gharghori et al. (2006)	Annual	Yes
Liquidity	Current Assets / Current Liabilities	CA / CL	Castagna and Matolscy (1981) Gharghori et al. (2006)	Annual	No
Leverage	Total Liabilities / Total Assets	TL / TA	Shumway (2001) Gharghori et al. (2006)	Annual	Yes
Cash flow generating ability	Net Cash Flow from Operations / Total Assets	CF / TA	Jones and Hensher (2004)	Annual	Yes
<b>Market-based Variables</b>					
Market-to-Book Ratio	Market Capitalization / Total Equity	MB	Gharghori et al. (2006) Campbell et al. (2008)	Annual	Yes
Firm Relative Size	Log (Firm Market Capitalization <sub>it</sub> / Total ASX Market Value <sub>t</sub> )	RSIZE	Shumway (2001) Campbell et al. (2008)	Annual	Yes
Market Leverage	Market Capitalization / Total Liabilities	MC / TL	Altman (1968) Shumway (2001) Gharghori et al. (2006)	Annual	Yes
Firm's Past Excess Return	$r_{i,t-1} - r_{m,t-1}$	EXRETURN	Shumway (2001) Campbell et al. (2008)	Annual	No
Market Sensitivity	Stock Price Volatility	SIGMA	Shumway (2001) Campbell et al. (2008)	Annual	No

Shumway's (2001) and Campbell et al.'s (2008) market-based variables are also used in model estimation. The market-to-book (MB) ratio is commonly used as a proxy for growth opportunities (Rajan and Zingales, 1995; Baker and Wurgler, 2002; Faulkender and Petersen, 2005). Campbell et al. (2008) demonstrated that MB has a positive effect on the risk of failure "when market value is unusually high relative to book value" (p.11). Following Shumway (2001), the size measure used in this study is the value of the company relative to the value of all companies listed on the ASX. This variable is measured as  $\ln(\text{Firm Market Capitalisation}_{i,t} / \text{Total ASX Market Value}_t)$ , which is denoted as RSIZE. Market Capitalisation/Total Liabilities (MC/TL) is used as a measure of market leverage. Bigger values of this variable represent lower levels of leverage and it is expected that this variable will have a negative relationship with the risk of failure.

Shumway (2001) includes firms' past excess returns and stock returns volatility in the covariate set. However, these two market variables are excluded from our model as there are insufficient data on failed observations. There are only 24 failed observations with sufficient data in Datastream to compute excess returns and volatility.

### **3.3.4 Summary Statistics**

Table 3-3 presents descriptive statistics for annual observations of firm-specific predictor variables after the data filtering process described in Section 3.3.1. The minimum and maximum values reported in the table are calculated after truncation. The financial characteristics of non-failed firms are notably in contrast

with those of failed firms for most variables.<sup>14</sup> For example, failed firms are found to have lower levels of profitability, operating liquidity and cash flow compared to those of non-failed firms. Meanwhile, non-failed firms have a lower level of book leverage and a higher market-to-book ratio. The dispersion of financial ratios among failed firms is also wider than that of non-failed firms, as evidenced in the higher standard deviations.

The first panel in Table 3-3 (Panel A) shows descriptive statistics of firm-specific variables for all firm-year observations of the entire sample, while the other two panels (Panels B and C) report descriptive statistics for the estimation and holdout sample. The whole sample includes information for 1,703 non-financial firms where 11,573 firm-year observations are obtained with 133 failure events. The second panel shows summary statistics for all firm-year observations of the estimation sample. There are a total of 1,267 firms and 6,934 firm-year observations in the estimation sample, of which 87 are failure observations. The holdout sample, as shown in the third panel, contains information for 1,455 firms with 4,639 firm-year observations, where there are 46 failure observations.

Table 3-3 shows that on average, profitability (NI/TA) is negative for the whole sample, even for the group of non-failed firms, which implies the active Australian companies have been experiencing 20% losses on average from 1995 to 2006. However, this is not a result of poor profits in a specific period. Panel D in

---

<sup>14</sup> Wilcoxon (Mann-Whitney U) test is carried out for each variable to test the significance of differences of firm characteristics between failed and non-failed groups. The test shows the differences are statistically significant at the 1% level for all variables except for the WC/TA for the entire sample and the estimation sample, and at the 5% level for all variables, with the exception of WC/TA, for the holdout sample.

Table 3-3 shows that profitability, on average, has been negative across all years in the sample. This result is attributed to the fact that it is driven by small firms. The value-weighted mean for NI/TA (not reported here) is positive. As shown in Panel E of Table 3-3, if the sample is restricted to the top quartile of firms by size, the mean and median profitability are positive, whereas if the sample is limited to the top half of firms by size, the mean is negative but the median is positive.

**Table 3-3: Descriptive Statistics of Firm-Specific Variables**

This table shows summary statistics of firm-specific variables for firm-year observations of the ASX listed firms. Each firm has multiple observations according to firm age (duration). The data are reported after truncation of the top and bottom one percent of distribution for each variable. NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. Panel A shows summary statistics for all firm-year observations for the entire sample over the period of 1995 to 2006. There are a total of 1,703 non-financial firms and 11,573 firm-year observations in the sample. The description of Panel B is as for Panel A except that it applies to an estimation sample over the period of 1995 to 2002. There are a total of 1,267 non-financial firms and 6,934 firm-year observations in the sample. The description of Panel C is also as for Panel A except that it applies to a holdout sample for the period of 2003 to 2006. There are a total of 1,455 non-financial firms and 4,639 firm-year observations in the sample.

Panel A: Descriptive statistics for the entire sample							
Variables	Distress group	N	Mean	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	11,440	-0.2113	-0.0214	0.6333	-4.3934	0.3786
	Failed	133	-1.3751	-0.2150	4.7324	-36.6215	0.3057
WC / TA	Non-failed	11,440	0.0448	0.0089	0.1975	-0.7373	0.6931
	Failed	133	-0.1210	0.0073	0.8486	-4.6596	0.7887
TL / TA	Non-failed	11,440	0.3762	0.3454	0.3387	0.0048	2.1601
	Failed	133	1.0329	0.5850	1.9887	0.0092	14.3223
CF / TA	Non-failed	11,440	-0.0733	-0.0034	0.3192	-1.9001	0.4206
	Failed	133	-0.4447	-0.0666	1.7017	-10.6182	0.5881
MB	Non-failed	11,440	2.5028	1.5393	3.8137	-6.4046	25.9554
	Failed	133	1.3837	1.0521	6.1556	-24.8231	20.9888
RSIZE	Non-failed	11,440	-9.9007	-10.249	2.0450	-13.4550	-4.2356
	Failed	133	-10.567	-10.629	1.7811	-14.3164	-5.4669
MC / TL	Non-failed	11,440	22.682	3.6451	53.5393	0.1109	368.2454
	Failed	133	16.426	1.4309	72.2129	0.0061	573.3985

Panel B: Descriptive statistics for estimation sample							
Variables	Distress group	N	Mean	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	6,847	-0.1983	-0.0118	0.5985	-4.0460	0.3069
	Failed	87	-0.7708	-0.1507	1.8185	-10.924	0.3057
WC / TA	Non-failed	6,847	0.0579	0.0177	0.1954	-0.6431	0.7296
	Failed	87	-0.0978	0.0476	0.8724	-4.6596	0.8152
TL / TA	Non-failed	6,847	0.3812	0.3694	0.3153	0.0045	1.8801
	Failed	87	0.9143	0.5890	1.6906	0.0092	14.3224
CF / TA	Non-failed	6,847	-0.0531	0.0051	0.2791	-1.6299	0.3890
	Failed	87	-0.2797	-0.0394	1.3287	-10.588	3.1345
MB	Non-failed	6,847	2.2376	1.3472	3.3228	-4.5730	22.863
	Failed	87	1.3804	0.8772	6.0826	-26.4490	20.9888
RSIZE	Non-failed	6,847	-9.7719	-10.1222	2.0445	-13.3446	-4.1501
	Failed	87	-10.383	-10.4026	1.7987	-14.3164	-5.3528
MC / TL	Non-failed	6,847	20.6426	2.9206	52.3778	0.0861	364.4086
	Failed	87	6.6312	0.9641	18.0155	0.0020	118.8998
Panel C: Descriptive statistics for holdout sample							
Variables	Distress group	N	Mean	Median	Std. Dev.	Minimum	Maximum
NI / TA	Non-failed	4593	-0.2313	-0.0373	0.6925	-4.9642	0.4921
	Failed	46	-4.3772	-0.3663	18.6078	-122.1968	0.3667
WC / TA	Non-failed	4593	0.0238	-0.0009	0.2046	-0.9616	0.5967
	Failed	46	-1.2710	-0.0252	8.1961	-55.5719	0.7085
TL / TA	Non-failed	4593	0.3697	0.3047	0.3792	0.00543	2.5779
	Failed	46	2.1730	0.5696	8.3126	0.0019	56.4481
CF / TA	Non-failed	4593	-0.1040	-0.0221	0.3753	-2.2797	0.4554
	Failed	46	-1.5850	-0.1037	7.6858	-51.2559	0.5881
MB	Non-failed	4593	2.9034	1.8408	4.5570	-9.2704	30.9598
	Failed	46	3.3070	1.1888	17.2088	-24.8231	110.8061
RSIZE	Non-failed	4593	-10.0927	-10.4478	2.0304	-13.5532	-4.3916
	Failed	46	-10.9148	-11.1065	1.7290	-14.4916	-7.2078
MC / TL	Non-failed	4593	25.7876	5.0740	55.5035	0.1332	375.5103
	Failed	46	38.3199	1.8335	135.5378	0.0239	728.3660

Panel D: Descriptive Statistics of NI/TA grouped by Year				
Year	N	Mean	Median	Std. Dev.
1995	674	-0.1155	0.0190	0.5374
1996	728	-0.0774	0.0132	0.3641
1997	773	-0.1080	0	0.4014
1998	806	-0.1733	0	0.6198
1999	873	-0.1681	0	0.5646
2000	992	-0.1396	-0.0049	0.4931
2001	1,034	-0.3593	-0.0401	0.9277
2002	1,054	-0.3696	-0.0649	0.9007
2003	1,061	-0.3203	-0.0386	0.8473
2004	1,128	-0.2209	-0.0294	0.7211
2005	1,210	-0.2237	-0.0410	0.6274
2006	1,240	-0.2827	-0.0384	1.5482

Panel E: Descriptive Statistics of NI/TA grouped by Firm Size (Quartile 1= Small firms)				
Quartile	N	Mean	Median	Std. Dev.
1	2893	-0.5247	-0.1765	1.1743
2	2893	-0.2784	-0.0794	0.9163
3	2893	-0.0939	0.0137	0.3983
4	2894	0.0341	0.0499	0.1886

It is noted that not all public firms have complete accounting and market information available for estimating the parameters of the model. In this study, any firm-year observations with incomplete data are eliminated from the final sample. Therefore, Table 3-3 only contains statistics for variables where there are no missing values. This was done for two reasons. Firstly, handling missing values causes substantial computational problems and, secondly, including missing value observations is likely to lead to informative censoring, as will be discussed below.

In relation to defaulting firms Sobehart and Stein (2000) state, “financial and market information are less likely to be complete or reliable in the time period leading up to default” (p.12). Therefore missing data may be an indicator of failure.

Observations with and without missing values are compared using the Mann-Whitney test. The result shows that the missing data are associated with firms that have more negative profits, higher leverage, and more negative cash flow. It appears that observations with missing data are financially weaker than those with complete data and therefore firms with missing observations are more likely to fail.<sup>15</sup> If this is true and these firms were included in the study in instances when data were available and then treated as censored when data were unavailable, this would give rise to informative censoring. In other words, it would induce the censoring substitutes for the failure event, and this violates the assumptions underlying the analysis.

Correlation matrices of the seven covariates in the model are constructed for the entire sample, the estimation sample and the holdout sample, respectively (see Table 3-4). The Pearson Product-Moment correlations are examined. All of the correlations are statistically significant at the 1% level, but the correlations are not so large as to cause serious concerns about collinearity. The highest correlation at about 0.65 is between Net Income/Total Assets and Net Operating Cash Flow/Total Assets.

---

<sup>15</sup> It is noted, however, that those firms not found to carry any information such that these firms were liquidated, went into receivership, or were delisted for failure to pay fees.

**Table 3-4: Correlation Matrix of Firm-Specific Variables**

This table presents the Pearson Product-Moment correlations, which are computed from observations with non-missing values for each pair of predictor variables. All correlations are significant at the 1% level (two-sided test). NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. Panel A shows the correlation matrices constructed based on the entire sample of 11,573 all firm-year observations over the period of 1995 to 2006 including 133 failed firms. Panel B is constructed using the estimation sample, where there are 6,934 firm-year observations over the period of 1995 to 2002, including 87 failed firms. Panel C is constructed on a holdout sample, where there are 4,639 firm-year observations over the period of 2003 to 2006, including 46 failed firms.

Panel A: Correlation matrix for the entire sample							
Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.355	-0.329	0.652	-0.063	0.258	-0.053
WC / TA			-0.301	0.300	-0.057	0.108	0.015
TL / TA				-0.169	-0.080	0.069	-0.311
CF / TA					-0.123	0.333	-0.136
MB						0.120	0.229
RSIZE							-0.112
MC / TL							
Panel B: Correlation matrix for estimation sample							
Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.331	-0.253	0.666	-0.052	0.290	-0.049
WC / TA			-0.254	0.240	-0.046	0.082	0.040
TL / TA				-0.079	-0.075	0.073	-0.321
CF / TA					-0.110	0.326	-0.142
MB						0.138	0.238
RSIZE							-0.103
MC / TL							
Panel C: Correlation matrix for holdout sample							
Variables	NI / TA	WC / TA	TL / TA	CF / TA	MB	RSIZE	MC / TL
NI / TA		0.401	-0.416	0.642	-0.070	0.230	-0.058
WC / TA			-0.386	0.382	-0.058	0.136	-0.020
TL / TA				-0.281	-0.083	0.059	-0.295
CF / TA					-0.126	0.341	-0.123
MB						0.118	0.208
RSIZE							-0.117
MC / TL							

In addition to the above firm-specific predictor variables, macroeconomic variables will be included in the model in later analysis. Four leading indicators of broad economic conditions are considered in this study: the ASX All Ordinaries Index, yield spread, the consumer confidence index and the consumer price index (inflation effect), and references to give theoretical justification to choice of these variables are provided in Table 6-1. Full details and descriptive statistics are given in Chapter 6 (Section 6.4.1).

Furthermore, it should be noted that Chapter 6 will be using a transformation of these variables that accounts for the non-linear relation between the variables and the risk of financial distress. Details of data transformation will be provided in Section 6.3.2.

### **3.4 Model Evaluation Approaches**

#### **3.4.1 Discrimination and Precision**

A model's predictive ability can be commonly assessed within two dimensions: discrimination and precision. Discrimination refers to the model's ability to distinguish between those companies surviving and those failing at a given point in time. Conversely, precision measures how well the estimated probability of a failure event matches true observation of the event.

#### **3.4.2 Receiver Operating Characteristics (ROC)**

To assess the discriminatory power of the models, the survival probabilities is used to classify each firm as failing or surviving, and then compare the classification

with the actual outcome. When the probability prediction is converted to a state prediction, picking the optimal cut-off value becomes an issue. Using ROC curves is one way to bypass the problem of determining an optimal cut-off point, since it examines the predictive power of the model across the entire spectrum of possible cut-off points (Partington et al., 2001).

The receiver operating characteristics (ROC) curve is a flexible method for representing the skill of a forecast system in types of dichotomous (binary), categorical, continuous and probabilistic forecasts. The method presents ratios that measure the proportions of events and non-events for which predictions (forecasts) are provided (Mason and Graham, 1999). For the current study, binary forecasts (prediction) are made based on whether a firm will be classified as either failing (event) or surviving (non-event). For a binary forecast of an event, a classification matrix can be constructed as illustrated in Table 3-5 (Mason and Graham, 1999).

**Table 3-5: Classification Matrix for Verification of a Binary Forecast System**

The following outcomes are possible:  $h$  is the number of hits;  $f$  is the number of false alarms;  $m$  is the number of misses; and  $c$  is the number of correct rejections. The hit rate,  $H$ , is equal to  $h / (h + m)$ , while the false alarm rate,  $F$ , is equal to  $f / (f + c)$ .

Forecasts (Predictions)	Observations		Total
	Event (E)	Non-event (E')	
Event prediction (P)	$h$	$f$	$p$
Non-event prediction (P')	$m$	$c$	$p'$
Total	$e$	$e'$	$n$

Out of a total number of  $n$  observations, the total number of events is provided as  $e$  and non-events as  $e'$ ; the total number of event predictions is given by  $p$  and non-event predictions by  $p'$ . There are two ways to obtain the correct forecast: (i) a hit, if the event occurs and the correct prediction for that event is provided ( $h$  is the number

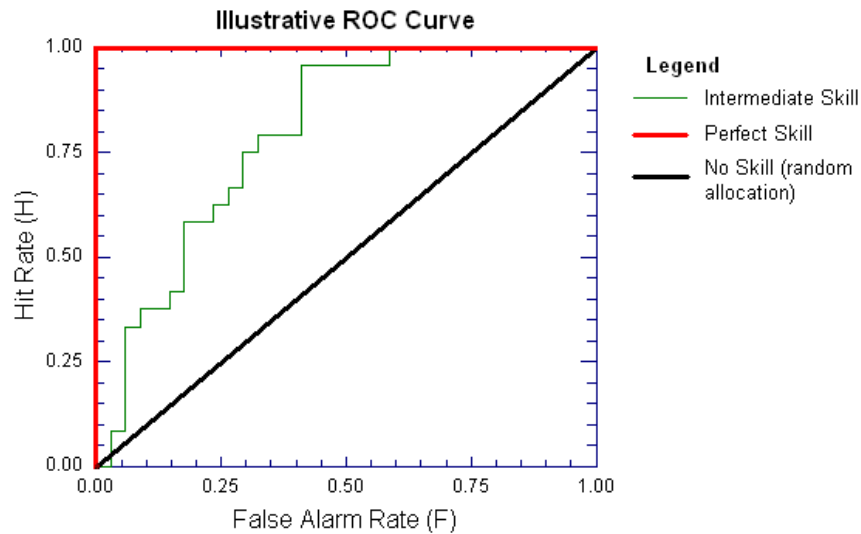
of hits) and (ii) a correct rejection, if the event is correctly forecasted not to occur ( $c$  is the number of correct rejections). Furthermore, two types of incorrect forecasts are also possible: (i) a false alarm, if an event does not occur but is incorrectly forecasted to occur ( $f$  is the number of false alarms) and (ii) a miss, if an event occurs but is incorrectly forecasted not to occur ( $m$  is the number of misses).

The ROC curves for predictive accuracy of a particular model are determined by the hit rate ( $H$ ) and the false alarm rate ( $F$ ). The hit rate,  $H$ , represents the proportion of observed events that are correctly forecasted and the false alarm rate,  $F$ , indicates the proportion of non-events that are incorrectly forecasted. Both ratios can be drawn simply from the classification matrix in Table 3-5:

$$\text{hit rate } (H) = \frac{h}{h+m} = \frac{h}{e} \quad (3-11)$$

$$\text{false alarm rate } (F) = \frac{f}{f+c} = \frac{f}{e'} \quad (3-12)$$

The ROC curves plots combinations of the false alarm rate (X-axis) and the hit rate (Y-axis) as the cut-off point is varied across all possible values. The model sustains perfect discriminating power when the hit rate ( $H$ ) equals one and the false alarm rate ( $F$ ) comes to zero and the ROC curve would plot in the upper left quadrant (red line, Figure 3-2). The 45-degree line, which is called a no discrimination line, shows the ROC curve for random forecasts between events and non-events (black line, Figure 3-2). Models which plot on this line have no forecast skill. The green line (Figure 3-2) represents a model with predictive power.



**Figure 3-2: Illustrative Receiver Operating Characteristic (ROC) Curve**

This figure provides examples of ROC curves representing intermediate skill (green line), perfect skill (red line) and no skill (black line).

Since the power of forecast skill increases as the ROC curve moves up and towards the left (maximising the number of hits ( $h$ ) and minimising the number of false alarms ( $f$ )), the hit rate ( $H$ ) and the false alarm rate ( $F$ ) together give a useful summary of the quality of binary forecasts.

Additionally, the predictive power of the model can be quantified by examining the area under the ROC curve (AUROC). AUROC is one of the most commonly used indices for evaluating performance and is also known as the ROC score. An AUROC of 1 represents a model with perfect discriminating power, whereas an AUROC of 0.5 indicates that a model has no discriminating power, which is equal to random forecasts. Therefore, a model with predictive power will have an AUROC of greater than 0.5 (Mason and Graham, 1999).

### 3.4.3 Scoring Rule (Brier Score)

A proper scoring rule is also used, known as the Brier Score, to assess the model's performance. While the ROC curves can be used to measure the model's ability to discriminate between those companies surviving and those failing at a given point in time, the Brier Score measures the model's precision, that is, the prediction accuracy at the level of the individual company. By calculating the deviation between the predicted probability of a failure event and the actual outcome of the event, the Brier Score shows the relationship between the model's prediction and the actual observation of company's status. The Brier Score is calculated as follows:

$$B = \frac{\sum_{n=1}^N (p_n - a_n)^2}{N}. \quad (3-13)$$

Where  $N$  is the number of predictions,  $p_n$  is the predicted probability that a failure event will occur and  $a_n$  is the actual observation of the event. When a firm fails, then  $a_n$  equals 1, otherwise it is 0. A Brier score of 1 indicates that the model has no predictive power and a score of 0 shows perfect predictive ability. Thus, the lower the Brier Score, the better the model's predictive power.

## 3.5 Conclusion

In summary, a proportional Cox hazards model is introduced to the study sample with seven firm-specific predictor variables. The study sample consists of financial data on ASX listed firms in the period between 1995 and 2006. The estimation sample includes eight years of data from 1995 to 2002 and the remaining data are used as the holdout sample. The variables considered in this study measure

the firm's profitability, leverage (book and market), liquidity, cash flow generating ability, relative size and growth opportunities. For the purpose of validation, receiver operating characteristics (ROC) curves and the Brier Score are introduced to evaluate the model's predictive power.

Henceforth, discussions in subsequent chapters will be based upon the data and methods presented in this chapter. This will include further extensions on the data and methods as well as an examination of the research questions stemming from those in Chapter 2.

## **CHAPTER 4: PREDICTING FINANCIAL DISTRESS – WHICH APPROACH IS BEST?**

### **4.1 Introduction**

Chapter 2 reviews the advances in distress prediction. This chapter will provide empirical evidence on the impact of these advances on the predictive capacity of the financial distress prediction models. The empirical modelling is undertaken using data from Australian listed companies.

To recapitulate, the aim of this thesis is to capture the changes of firms' financial characteristics over a longer period of time and accordingly measure the changing probability of firms' level of risk for financial distress. As will be discussed in Section 4.2.3, the objective is to incorporate the "accumulating impact of financial performance" (Jones and Hensher 2004, p.1031). In the past, most researchers have been taking observational data of the firm's characteristics one year before the event (or the point of time for prediction) to calculate default probabilities for the following year. In most banks, credit risk assessments are reviewed annually or bi-annually, therefore forecasting financial distress for a one-year horizon is consistent with these reviews. However, when a loan is first considered, the corresponding credit assessment is presumably valid for the term of the loan, which may be for many years. Consequently, models are required to assess the risk of financial distress over extended time horizons.

Three major issues that have been identified from the literature review are tackled in this chapter. Firstly, how to utilise multiple-year financial data for the firm in estimating a model for corporate failure prediction, and whether using such observations enhances the predictive power of the model. Secondly, whether the addition of market-based information to accounting data increases the predictive power of the model. Thirdly, whether the inclusion of lagged changes in financial ratios improves the predictive power of the model.

The remainder of the chapter is organised as follows. The next section (4.2) examines the approach to constructing the models. Section 4.3 discusses the data and evaluation techniques to be used. Section 4.4 presents empirical results and Section 4.5 concludes the chapter and provides suggestions for further research.

## **4.2 Multiple-Period versus Single-Period Models**

### **4.2.1 Why is the Multiple-Period Approach Preferred?**

Traditional statistical models utilise the firm's financial data from the year before the event of a company failure. Given the company's financial characteristics at a point in time, the model makes a dichotomous decision whether the company will experience a failure event or not. It is noted that these models can only include a single set of predictor variables for each company. Shumway (2001) referred to these single-period classification models as static models. Given that the static models ignore the fact that financial characteristics of most companies change through time, recent empirical studies have pointed out that making predictions in a static setting

contains sample selection biases and thus results in inconsistent parameter estimations (Shumway, 2001; Hillegeist Keating, Cram and Lundstedt, 2004).

This limitation of static models motivated academic research to pursue alternative estimation models that account for the variation in financial distress dynamics. Including multiple firm-year observations in the financial distress model, one can avoid the sample selection problem referred to above. Secondly, when the concept of a company's life span or duration is introduced, the model can control for the period at risk for each company. This will distinguish those companies that have been in the study period for many years from those with a shorter period. Thirdly, it enables the model to account for changes contributing to the underlying risk of financial distress over time, and thus provide the prediction result as a function of time and financial performance.

#### **4.2.2 Multiple-Period Model Construction**

Here, the empirical question is whether employing multiple firm-year observations as model inputs will lead to better predictive accuracy than a model with a single firm-year observation.

In order to test this, a single-period logit model is estimated and compared to a multiple-period hazards model. A single-period logit model is a widely used static technique in traditional financial distress literature.<sup>16</sup> An estimation sample is obtained by selecting a firm-year set of observations collected immediately prior to the failure event from failed firms as well as the latest firm-year observation dataset for active

---

<sup>16</sup> Details of a logit model can be found in Section 2.3.2.3 in this dissertation.

firms. For the holdout sample, a firm-year observation is randomly selected for each active and failed firm from out-of-sample data.

As recalled from equation 2-2 in Chapter 2, a logit model can be written as:

$$P_i = \frac{1}{1 + e^{-(\alpha + \beta z)}} , \quad (4-1)$$

where  $P_i$  is the probability that a firm  $i$  experiences financial distress. It is noted that in a single-period logit model, each firm contributes only one observation. For each observation,  $z$  is a vector of predictor variables such that  $z_j^i$  refers to the value of the  $j$ th variable for the  $i$ th firm.  $\beta$  is a vector of coefficients with  $\beta_j$  the coefficient for  $z_j$ .

In contrast, a multiple-period model is able to make use of all available data. Therefore, in the Cox regression (survival model) each company is allowed to retain multiple firm-year observations over time according to its life span (duration), forming a panel dataset. For instance, if a company has operated for 10 years, there would be 10 different data records created for the company.

To reiterate the equation 3-2 in Chapter 3, the Cox model is written as:

$$h_i(t | z) = h_0(t) \cdot \exp \left\{ \sum_{j=1}^p \beta_j z_j^i \right\} , \quad (4-2)$$

where  $h_i(t | z)$  is the hazard for firm  $i$  at time  $t$ .  $z$  is a row vector of measured covariates ( $z_j^i$  denotes the value of the  $j$ th covariate for the  $i$ th firm) and  $\beta$  is a column vector of parameters with the appropriate dimensions ( $\beta_j$  is the corresponding coefficient for  $z_j^i$ ).

### **4.3 Accounting-Based versus Market-Based Variables**

#### **4.3.1 Do Market-Based Variables Predict the Company Failure Better?**

As discussed in Section 2.4.1, the use of market-based variables has been increasingly advocated in improving the predictive power of financial distress models. The empirical findings from Shumway (2001) and Chava and Jarrow (2004) even demonstrate that accounting-based data are barely statistically significant in explaining financial distress and add little if any predictive power once the market data are included in the model.

On the other hand, the significant role of accounting-based data is still upheld by some studies such as Campbell et al. (2008) where little difference is found in the predictive abilities between models with and without market data. Likewise, Reisz and Perlich (2007) and Argarwal and Taffler (2008) support the use of accounting information for predicting corporate failures.

#### **4.3.2 Models with Accounting-Based and Market-Based Variables**

Three different models are studied to address the issue of market versus accounting variables. Firstly, a model is estimated solely using accounting-based variables (*Model 1*) and a second model (*Model 2*) is built only on market-based variables. Market-based variables reflect measures of publicly traded equity value. *Model 3* employs both the accounting-based and market-based variables.

These three models are applied to the main models constructed in Section 4.2.2, including the single-period logit model and the multiple-period Cox model. In

other words, there are three models for the single-period logit model and another three models for the multiple-period Cox model.

#### **4.4 Models with and without Lagged Changes**

##### **4.4.1 Is Company Failure a Sudden Event or a Historical Outcome?**

There still remains the question as to whether corporate failure is a sudden event of financial deterioration in a single year or a process of historical events entailing “an accumulating impact of the financial performance leading up to failure on the response outcome” (Jones and Hensher 2004, p.1031). Consequently, one of the goals of this study is to develop a model able to reflect history, and so detect any trend or a sustained decline in financial performance. This study suggests that lagged changes of a variable may be entered as input variables to the financial distress prediction models (Hillegeist et al. 2004; Jones and Hensher, 2004).

##### **4.4.2 Models with Lagged Changes of Predictor Variables**

Two models are estimated for the purpose of examining the impact. One is named as *Levels Model*, which only contains the level variables ( $x_t$ ), and the other is *Lagged Change Model*, where both the level variables and the lagged change variables ( $\Delta x_t$ ) are included. Lagged change variables measure the change in values between successive years, that is the delta of the variable between two periods ( $\Delta x_t = x_t - x_{t-1}$ ). Three consecutive firm-year observations are employed to make this achievable. The lagged changes model includes a level variable at time  $t$  ( $x_t$ ), a lagged variable of an annual change between time  $t$  and  $t-1$  ( $\Delta x_t$ ), and another lagged variable of an annual change between time  $t-1$  and  $t-2$ , ( $\Delta x_{t-1}$ ).

Both models are constructed based on the multiple-period Cox proportional hazards model, which was specified in Equation 4-2 above in Section 4.2.2.

As a consequence, the *Levels Model* is a duplicate to the multiple-period Cox hazards model developed to compare static and multiple-period models. The predictive accuracy of the *Levels Model* and *Lagged Change Model* are compared in Section 4.6.2.

## **4.5 Data and Evaluation Methods**

As documented in Section 3.3, firm-specific accounting-based and market-based variables are used to construct the aforementioned models for Australian listed companies during the time period between 1995 and 2006. Receiver operating characteristic (ROC) curves are used to assess the model's predictive accuracy in terms of discriminative power.

## **4.6 Results**

### **4.6.1 Results for the First Two Research Questions**

The first and the second research questions are examined together. *Models 1* to *3* are estimated from a sample of up to 6,934 firm-year observations for the period of 1995 to 2002, with 87 failure observations. These three models (models with accounting-based only, market-based only and both variables) are constructed based on a single-period setting as well as a multiple-period setting. Table 4-1 presents the parameter estimates and the goodness of fit measure of the single-period logit model with *Model 1*, *2* and *3* and those of the multiple-period hazards model are presented in

Table 4-2. Panel A in each table shows the total number of firms used in estimating the model parameters, and each number of failed and non-failed firms. The resulting coefficient estimates of the three models are shown in Panel B, with their expected signs and their respective  $p$ -values (based on a chi-squared statistic for the significance of each coefficient).<sup>17</sup> Panel C provides an in-sample goodness of fit measure.

In Panel B of Table 4-1, the result of *Model 1* with a single-period firm-year observation shows that firms with higher profitability and higher level of book leverage are significantly more likely to fail while firms with higher cash flow generating ability are less likely to fail. The relation between profitability and the risk of financial distress is contrary to the expected signs. A positive coefficient for NI/TA is contradictory to the intuition that higher net income is associated with lower risk of failure. In *Model 2*, the firm's relative size and market leverage (RSIZE and MC/TL) are statistically significant with the expected signs. The results of *Model 3* show that increased profitability and higher book leverage increase the risk of failure, while higher cash flow generating power, larger relative size and more market value relative to debt reduce the risk of failure. The profitability variable (NI/TA) is still found to be significantly positively related to the risk of failure.

When *Model 1* is estimated with multiple-period firm-year observations, as shown in Panel B of Table 4-2, the magnitudes of the coefficients are noticeably different and profitability (NI/TA) loses its significance, while operating liquidity (WC/TA) becomes a significant variable. A higher level of operating liquidity

---

<sup>17</sup> The  $p$ -values are based on a Wald test-statistics as given by the squared ratio of the estimated coefficient to its estimated standard error.

increases the risk of financial distress. This result is counterintuitive; however, WC/TA is not significant in multi-period *Model 3*. Multi-period *Model 2* has similar parameter estimates to those of a single-period model, indicating that a larger relative size with a higher level of market leverage leads to a lower risk of failure. Multi-period *Model 3* has the same significant variables as the single-period *Model 3*, with the exception of profitability which is insignificant.

**Table 4-1: Single-Period Logit Model Estimates for *Model 1, 2 and 3***

Panel A shows the total number of firms, the number of failed firms and the number of non-failed firms and percentages of non-failed to the total number of firms in the estimation sample over the period of 1995 to 2002. Panel B reports the parameter estimates of single-period logit models with and without market variables. NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable. The goodness of fit of each model is presented in Panel C.

\*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%

Panel A: Number of failed and censored firm-year observations in the estimation sample				
Total	Failed	Non-failed	Percent Non-failed	
1,267	87	1,180	93.13	
Panel B: Parameter estimates				
Variables	Expected Sign	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>
Intercept		-3.1714	-4.5496	-4.3282
NI / TA	-	0.3658***		0.2820***
WC / TA	-	0.4645		0.3154
TL / TA	+	1.1024***		0.7905***
CF / TA	-	-1.6973***		-1.4548***
MB	+		0.00126	0.0049
RSIZE	-		-0.5090***	-0.3520**
MC / TL	-		-0.0214**	-0.0248**
Panel C: Model Goodness of fit				
	Intercept only	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>
-2 LOG L <sup>1</sup>	560.943	516.451	535.450	501.289
Likelihood Ratio <sup>2</sup>		44.4920***	25.4925***	59.6538***
Degrees of Freedom		4	3	7

<sup>1</sup> The term -2 LOG L indicates the logarithm of the maximum likelihood estimator for the model. It measures the goodness of fit of the presented model, and smaller values indicate a more desirable model.

<sup>2</sup> The likelihood ratio tests the null hypothesis that all coefficients except for the constant are zero. The test statistic ( $\lambda$ ) is calculated as  $\lambda = -2(\ln L_0 - \ln L)$ , where  $\ln L_0$  is the log likelihood of the restricted model only with an intercept and  $\ln L$  is the log likelihood of the estimated model with parameters.

**Table 4-2: Multiple-Period Hazards Model Estimates for Model 1, 2 and 3**

Panel A shows the total number of firms, the number of failed firms and the number of censored (non-failed) firms and percentages of censored to the total number of firms in the estimation sample over the period of 1995 to 2002. Panel B reports the parameter estimates of multiple-period Cox hazards models with and without market variables. NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable. Panel C shows each model's goodness of fit.

\*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%

Panel A: Number of failed and censored firm-year observations in the estimation sample				
Total	Failed	Censored	Percent Censored	
6,934	87	6,847	98.74	
Panel B: Parameter estimates				
Variables	Expected Sign	Model 1	Model 2	Model 3
NI / TA	-	0.04323		0.04221
WC / TA	-	0.25528**		0.19394
TL / TA	+	0.29935***		0.24230***
CF / TA	-	-0.11693**		-0.10483**
MB	+		0.00039	0.00188
RSIZE	-		-0.36116***	-0.31158**
MC / TL	-		-0.02273**	-0.01954**
Panel C: Model Goodness of fit				
	Without Covariates	Model 1	Model 2	Model 3
-2 LOG L <sup>1</sup>	1132.852	1118.760	1114.120	1104.478
Likelihood Ratio <sup>2</sup>		14.0925***	18.7315***	28.3736***
Degrees of Freedom		4	3	7

<sup>1</sup> The term -2 LOG L indicates the logarithm of the maximum likelihood estimator for the model. It measures the goodness of fit of the presented model, and smaller values indicate a more desirable model.

<sup>2</sup> The likelihood ratio tests the null hypothesis that all coefficients except for the constant are zero. The test statistic ( $\lambda$ ) is calculated as  $\lambda = -2(\ln L_0 - \ln L)$ , where  $\ln L_0$  is the log likelihood of the restricted model only with an intercept and  $\ln L$  is the log likelihood of the estimated model with parameters.

Table 4-3 compares the accuracy of the models for in-sample estimates and out-of-sample forecasts considered above. The out-of-sample forecast is measured with the holdout sample of 4,639 firm-year observations for the period of 2003 to 2006, where there were 46 failure observations. The area under the ROC (AUROC) curve measures the discriminative power of the model where the higher the AUROC, the better the model's performance (See Figure 4-1).

The in-sample AUROC in Panel A indicates that for both single-period and multi-period models *Model 3*, with both accounting-based and market-based variables, produces estimates that are the most accurate. Similarly, for the out-of-sample forecast (Panel B), the best forecast accuracy for single-period models as well as multiple-period models is attained when both accounting and market variables are used.

Based on the results from in-sample estimates (Panel A in Table 4-3), none of the multiple-period models perform better than the corresponding single-period models.

However, out-of-sample forecasts (Panel B) show that the multi-period model provides forecasts that have greater discriminatory power than the single-period forecasts. All of the multiple-period models demonstrate higher predictive accuracy than their single-period counterparts; however, the differences in the AUROC are quite small. What is noticeable in Table 4-3 is that the in-sample estimate and out-of-sample forecast AUROCs are similar for the multi-period models, but there is a noticeable decline in AUROC for the out-of-sample forecast using the single period models. This latter result is consistent with the arguments of Shumway (2001) and

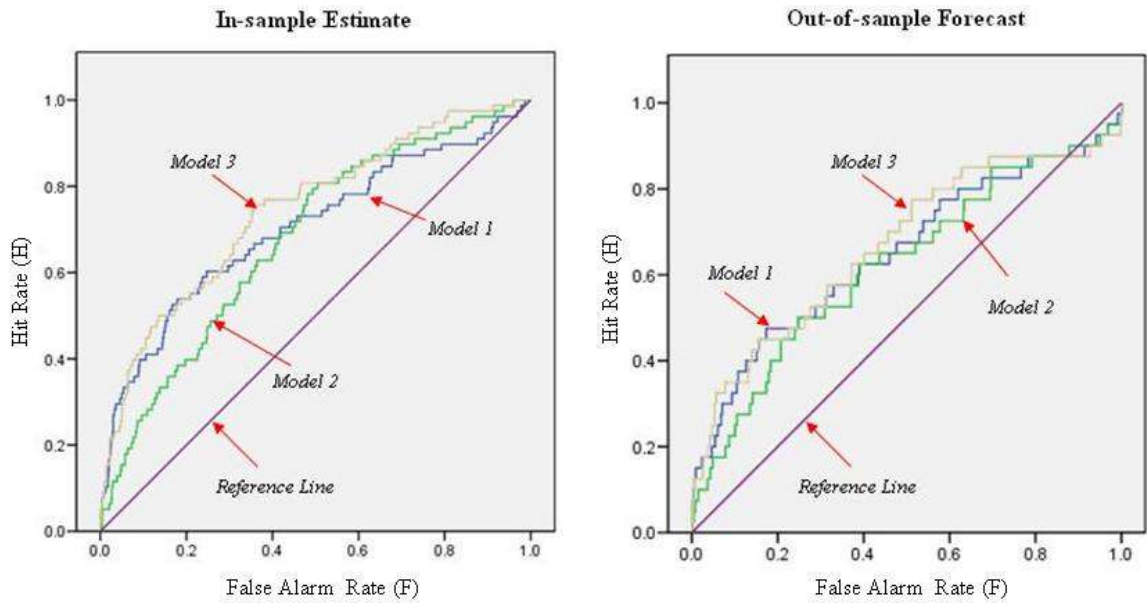
Hillegeist et al. (2004) that the single-period model is too sample-specific, restricting generalisability and potentially producing biased and inconsistent estimates of model coefficients.

**Table 4-3: Forecast Accuracy with the Area Under ROC Curve**

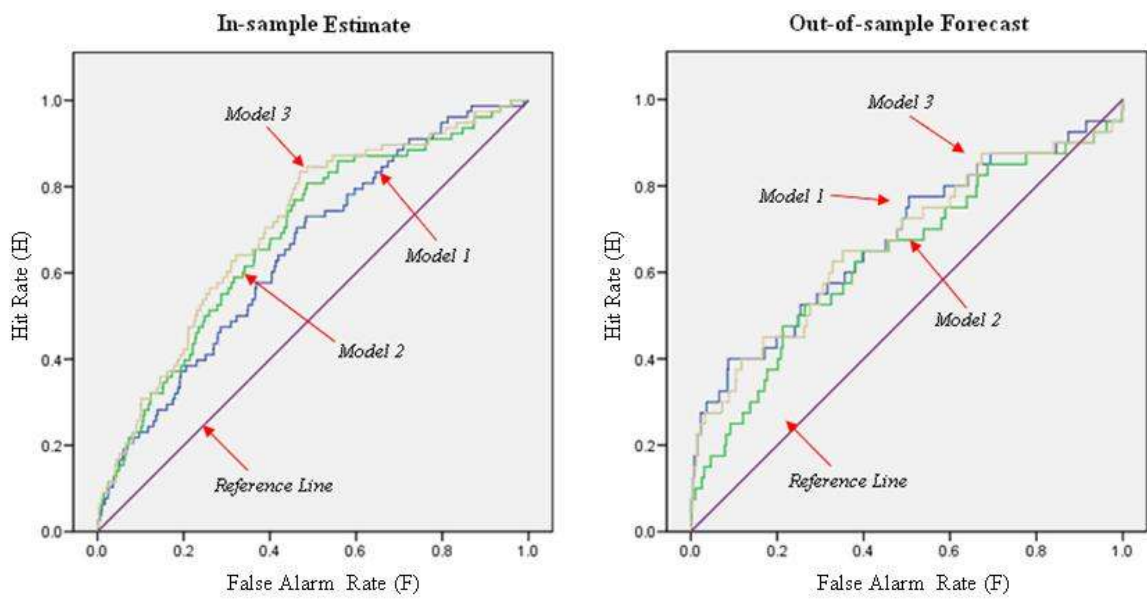
This table shows the area under ROC (AUROC) curve of the forecast accuracy of the models considered in Tables 4-1 and 4-2. The AUROC measures the discriminatory power of the model and the higher the AUROC, the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel A examines the in-sample estimate accuracy of a single-period logit model vis-à-vis a multiple-period Cox model across *Model 1*, *Model 2* and *Model 3* with the estimation sample from 1995 to 2002. Panel B shows the forecast accuracy for the holdout sample from 2003 to 2006.

Panel A: In-sample Estimate Accuracy			
	AUROC		
	Random Estimate	Single-Period Model	Multiple-Period Model
<i>Model 1</i>	0.5	0.703	0.679
<i>Model 2</i>	0.5	0.678	0.663
<i>Model 3</i>	0.5	0.744	0.683
Panel B: Out-of-sample Forecast Accuracy			
	AUROC		
	Random Forecast	Single-Period Model	Multiple-Period Model
<i>Model 1</i>	0.5	0.650	0.666
<i>Model 2</i>	0.5	0.623	0.637
<i>Model 3</i>	0.5	0.665	0.670

### Panel A: ROC Curves of a Single-Period Logit Model



### Panel B: ROC Curves of a Multiple-Period Hazards Model



**Figure 4-1: ROC Curves**

The figure illustrates the ROC curves generated by models considered in Tables 4-1 and 4-2. Panel A shows the in-sample estimate and out-of-sample forecast of a single-period logit model and Panel B presents the in-sample estimate and out-of-sample forecast of a multiple-period hazards model.

#### 4.6.2 Results for the Third Research Question

*Levels Model* with current levels variables ( $x_t$ ) and *Lagged Change Model* including both the current levels ( $x_t$ ) and lagged changes ( $\Delta x_t$  and  $\Delta x_{t-1}$ ) variables are estimated using the estimation sample (from 1995 to 2002) of up to 5,959 firm-year observations, with 76 failure observations. Observations of some firms have been withdrawn from the study as they do not have complete financial information for three consecutive years. As explained in Section 4.3.1, the *Levels Model* is identical to the multiple-period hazards model. Accordingly, Table 4-2 displays the estimation results of *Levels Models* and Table 4-4 shows the parameter estimates and the goodness of fit measure of *Lagged Change Models* with *Model 1*, *2* and *3*. Panel A in Table 4-4 shows the total number of firms used in estimating the model parameters, and each number of failed and non-failed firms. Panel B gives the resulting coefficient estimates of the models, with their expected signs and their respective  $p$ -values, while Panel C provides an in-sample goodness of fit measure.

The results for the *Lagged Change Model 1* (Table 4-4, Panel B) reveal that most variables are driven to insignificance, as lagged changes in the variables are included, with the exception of book leverage (TL/TA). In *Model 2*, the annual change in RSIZE variable between year  $t-1$  and  $t$  and the level of market leverage (MC/TL) are found to be statistically significant at the 5% level. The result of *Model 3* indicates that a higher level of book leverage increases the risk of failure whereas more market value relative to debt, growth in relative size over year  $t$  and an increase in market value relative to debt over year  $t-1$ , reduce the risk of failure as expected.

**Table 4-4: Hazards Model Estimates with Lagged Changes for Model 1, 2 and 3**

Panel A shows the total number of firms, the number of failed firms and the number of censored (non-failed) firms and percentages of censored to the total number of firms in the estimation sample over the period of 1995 to 2002. Panel B reports the parameter estimates of Lagged Change Models with and without market variables. NI/TA, WC/TA, TL/TA, CF/TA, MB, RSIZE, MC/TL indicate the current level of the variables.  $\Delta$  signifies the annual change between the variable at a particular time and the same variable in the previous year. Therefore,  $\Delta x_t$  denotes a lagged change between time  $t$  and  $t-1$ , and  $\Delta x_{t-1}$  represents a lagged change between time  $t-1$  and  $t-2$ . A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable. Panel C shows each model's goodness of fit.

\*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%

Panel A: Number of failed and censored firm-year observations in the estimation sample				
Total	Failed	Censored	Percent Censored	
5,959	76	5,883	98.72	
Panel B: Parameter estimates				
Variables	Expected Sign	Model 1	Model 2	Model 3
NI / TA	-	0.23514		0.24510
$\Delta$ NI / TA <sub>t</sub>	-	-0.15295		-0.15650
$\Delta$ NI / TA <sub>t-1</sub>	-	-0.20731		-0.20438
WC / TA	-	0.23469		0.19531
$\Delta$ WC / TA <sub>t</sub>	-	0.11643		0.00440
$\Delta$ WC / TA <sub>t-1</sub>	-	0.12567		0.16935
TL / TA	+	0.33501***		0.31590***
$\Delta$ TL / TA <sub>t</sub>	+	0.01345		-0.04870
$\Delta$ TL / TA <sub>t-1</sub>	+	-0.09321		-0.08865
CF / TA	-	-0.18744		-0.22916
$\Delta$ CF / TA <sub>t</sub>	-	0.08110		0.14149
$\Delta$ CF / TA <sub>t-1</sub>	-	-0.02163		0.02900
MB	+		-0.00654	-0.00328
$\Delta$ MB <sub>t</sub>	+		0.00849	0.00853
$\Delta$ MB <sub>t-1</sub>	+		0.00340	0.00572
RSIZE	-		-0.22984	-0.15192
$\Delta$ RSIZE <sub>t</sub>	-		-0.64767**	-0.70906**
$\Delta$ RSIZE <sub>t-1</sub>	-		-0.05508	-0.01312
MC / TL	-		-0.02176**	-0.01825**
$\Delta$ MC / TL <sub>t</sub>	-		0.00728	0.00473
$\Delta$ MC / TL <sub>t-1</sub>	-		-0.00267	-0.00302*
Panel C: Model Goodness of fit				
	Without Covariates	Model 1	Model 2	Model 3
-2 LOG L	1132.852	1102.260	1105.584	1079.583
Likelihood Ratio		30.5924***	27.2685***	53.2694***
Degrees of Freedom		12	9	21

The area under ROC curves (AUROC) is used to evaluate the model's performance. In-sample and out-of-sample accuracy are reported in Table 4-5. Both in-sample and out-of-sample the performance of the *Lagged Change Models* is superior to that of *Levels Models* for *Models 2* and *3*. *Model 3* results in the best predictive accuracy in the *Levels* and *Lagged Change Models*. Our conclusion from Table 4-3, indicating that the inclusion of both accounting-based and market-based variables in the financial distress model leads to a superior performance in distress forecasts, continues to hold even when the model is adjusted for lagged effects.

These results from both in-sample estimates and out-of-sample forecasts show that including lagged changes in the variables improves model performance when market-based variables are employed. However, there is a cost. The best model contains 21 variables (although only four are significant). This consumes degrees of freedom and it also increases the chances of problems with multicollinearity between the predictor variables.

**Table 4-5: Forecast Accuracy with the Area Under ROC Curve**

This table shows the area under ROC (AUROC) curve of the forecast accuracy of the models considered in the second and third research questions. The AUROC measures the discriminatory power of the model and the higher the AUROC, the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel A compares in-sample estimates accuracy of *Levels Model* vis-à-vis *Lagged Change Model* across *Model 1*, *2* and *3*. Panel B shows the out-of-sample forecast accuracy.

Panel A: In-sample Estimate Accuracy			
AUROC			
	Random Estimate	<i>Levels Model</i>	<i>Lagged Change Model</i>
<i>Model 1</i>	0.5	0.679	0.670
<i>Model 2</i>	0.5	0.663	0.684
<i>Model 3</i>	0.5	0.683	0.733

Panel B: Out-of-sample Forecast Accuracy			
AUROC			
	Random Forecast	<i>Levels Model</i>	<i>Lagged Change Model</i>
<i>Model 1</i>	0.5	0.666	0.625
<i>Model 2</i>	0.5	0.637	0.664
<i>Model 3</i>	0.5	0.670	0.686

## 4.7 Conclusion

This chapter examined some key issues addressed in recent studies of financial distress prediction and posed three research questions: (i) whether the use of multiple-period data improves the predictive power of the model, (ii) whether information on market-based variables can better predict financial distress, and (iii) whether the inclusion of the changes in variables over successive years increases the predictive power of the model. Based on the empirical results provided in this chapter, the following conclusions can be made:

- i) When the financial distress prediction model uses all available multiple firm-year observations of each company, it shows greater predictive power in out-of-sample forecast.
- ii) The empirical evidence does not support the argument that models using market-based variables outperform those using accounting-based variables. If anything the results suggest the reverse. However, the best performance for both in-sample estimates and out-of-sample forecasts was achieved by the models that used both accounting ratios and market variables.
- iii) A model incorporating lagged changes in variables is shown to provide a somewhat better forecast than models that contained only the current level of the predictor variables.

In relation to the assessment of the performance of the models, it is emphasised that only the ability of the models to discriminate between distressed and non-distressed firms was examined. While the models had some power in this respect, it cannot be claimed that their performance was outstanding. It is also the case that differences in performance between the models was quite modest. In subsequent chapters the assessment of the models will be extended to include a proper probability scoring rule. Efforts will also be directed to improving the out-of-sample performance.

# CHAPTER 5: TIME AND THE PREDICTION OF FINANCIAL DISTRESS

## 5.1 Introduction

Much of the previous work in financial distress prediction focuses on static predictions and uses static variables in estimating the predictive model. In this chapter the goal is to make dynamic predictions and to use dynamic variables in estimating the model. With dynamic predictions the probability of financial distress is allowed to vary over the forecast period. With dynamic variables the model estimation allows for changes in the financial characteristics of a firm over time.

The motivation for this chapter is threefold. Firstly, the dynamic forecasts of the probability vector for failure  $f_t$  to  $f_{t+n}$  (where  $f_t$  is the probability of failure at time  $t$ ) have been much less explored than the static forecast of a single failure probability  $f$ . Secondly, relatively little use has been made of dynamic forecasting variables. In most applications, including a data vector of, say, the last five years, profitability in forming a forecast requires five separate profitability variables in the model and this is not commonly done.<sup>18</sup> In the approach used in this study, the vector of data is represented by a single profitability variable. Thirdly, one of the most popular techniques for survival analysis is the Cox proportional hazards model (Cox, 1972). Unfortunately, for reasons discussed later, forming forecasts is problematic when a

---

<sup>18</sup> A more common approach, as exemplified by Altman (1968), is to estimate five separate models using data one year before the failure, two years before the failure and so on back to year five.

Cox proportional hazards model contains dynamic variables. In this study, a procedure is implemented to overcome this problem.

The work on estimating models which allows for time-varying probabilities of financial distress began in the mid-1980s (for example, Crapp and Stevenson, 1987). These models use the techniques of survival analysis and have attracted increasing attention following the dynamic model of Shumway (2001). Despite the growing use of survival analysis in modelling financial distress, relatively little attention has been given to the use of dynamic variables in estimating these models. Initially this was because of computational difficulties in estimating models with time-varying predictor variables, sometimes referred to as “time-dependent covariates” (Allison 1984, p. 36), and even when this problem was overcome, a problem remained in making forecasts when using the Cox model.

A key element in forecasts when using the Cox proportional hazards model is the baseline hazard. When making a forecast, the baseline hazard is scaled up, or down, according to the firm’s risk factors, and this scaled hazard is used to compute the probability of financial distress. When time-varying variables are introduced into the Cox model, forming estimates of the baseline hazard has been problematic. Consequently making forecasts has also been impracticable with time-varying variables in past financial distress studies.

However, the Cox model has been considerably used in medical studies. Chen, Yen, Wu, Liao, Liou, Kuo, and Chen (2005) applied the Cox model with time-varying variables to find the effect of biochemical covariates on death attributed to liver cancer. They implemented a method for estimating the baseline hazard and hence

were able to make survival forecasts with time-varying variables. Following the approach of Chen et al., a Cox regression model with time-varying covariates is constructed for the prediction of financial distress in this study.

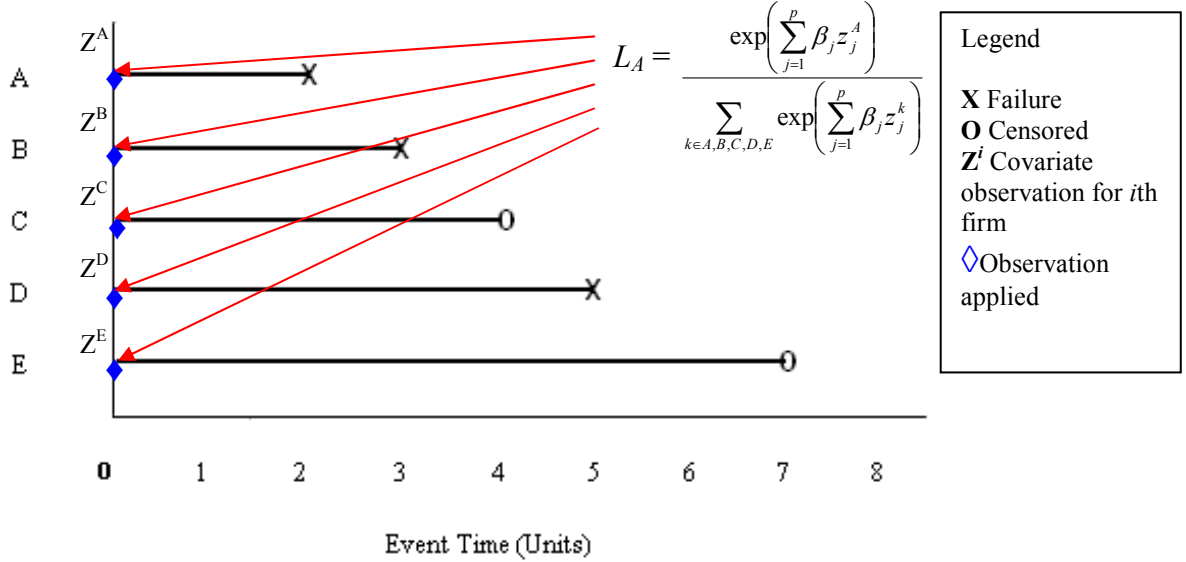
Using firm-specific data on Australian Securities Exchange (ASX) listed firms from 1995 to 2006, a time-varying Cox hazards model is developed with seven predictor variables measuring profitability, leverage (book and market), liquidity, cash flow, size, and growth opportunities. Each variable is allowed to make use of all available yearly data for firms that are in the estimation sample for the full eight years (from 1995 to 2002). Book leverage, cash flow generating ability and market leverage are found to be significant predictors of financial distress. Receiver operating characteristic (ROC) curves and the Brier Score show that the dynamic Cox model has modest predictive power, showing better out-of-sample forecasts than a static logit model.

The remainder of this chapter is set out as follows. Section 5.2 presents the methods to construct a Cox hazards model with time-varying variables. Section 5.3 describes the data. Section 5.4 presents the results of parameter estimates and is followed by an assessment of the predictive accuracy of the model. The final section concludes this chapter and offers some possible directions for future research.

## **5.2 A Cox Hazards Model with Time-Varying Covariates**

Figure 5-1 illustrates the process of coefficient estimation in a conventional Cox proportional hazards model, which was introduced in Section 3.2. It is noted that the vector of coefficients is estimated using the fixed covariate measures for each

individual (company) in the risk set, whose values remain invariant with respect to time. Therefore, the hazard ratio for any two given firms is constant over time.



**Figure 5-1: Estimation of the Likelihood for the Failure of Firm A in a Conventional Cox Proportional Hazards Model**

The figure above illustrates the arrangement of the data in forming the likelihood function in a time-invariant Cox model. Observations of A through E are arranged in event time. The vector of coefficient is estimated using the fixed covariate values at the beginning of the study. The length of the line indicates the life time of the observation. An “X” marked at the end of the line denotes the event of failure, whereas an “O” marker indicates that the observation has been censored for reasons other than failure.

The conventional Cox proportional hazards model can be extended to allow for predictor variables that change in value over time as follows (Andersen, 1992):

$$h_i(t | z(t)) = h_0(t) \cdot \exp \left\{ \sum_{j=1}^p \beta_j z_j^i(t) \right\}. \quad (5-1)$$

$h_i(t | z(t))$  is the time-varying hazard function for firm  $i$  at time  $t$ .  $z_j^i(t)$  denotes the value of the  $j$ th covariate at time  $t$  for the  $i$ th firm,  $\beta_j$  is the corresponding

coefficient for  $z_j^i$ , while  $h_0(t)$  is the baseline hazard representing the effect of a firm's lifetime on the hazard without covariates.

In most previous bankruptcy literature, each annual observation of a firm has been treated as an independent observation and therefore researchers could not take advantage of all the available multiple-year financial information. Using Equation 5-1, the model is able to “exploit each firm's time-series data by including annual observations as time-varying covariates” (Shumway 2001, p.102). That is, if a firm has been observed for 12 years in the set of firms potentially at risk of financial distress, the values of each covariate  $z_j^i(t)$  for that firm are allowed to be updated up to 12 times from year to year ( $t$ ). Consequently, it is possible to retain multiple-year financial information for each firm according to its lifetime (or duration) and make use of all the time-series data within the period to estimate the model's coefficients.

In the Cox hazards model with time-varying covariates, the value of covariates  $z_j^i(t)$  changes with time. The hazard at time  $t$  depends on the value of covariates at time  $t$  ( $z_j^i(t)$ ) and therefore the hazard ratio ( $HR$ ) also varies with time. The definition is as follows.

$$HR(t | z(t)) = \frac{h_i(t | z(t))}{h_0(t)} = \exp\left\{\sum_{j=1}^p \beta_j z_j^i(t)\right\}. \quad (5-2)$$

Thus, unlike the conventional Cox proportional hazards model where the hazard ratio remains constant, the proportionality assumption in the Cox hazards model with time-varying covariates is no longer maintained.<sup>19</sup>

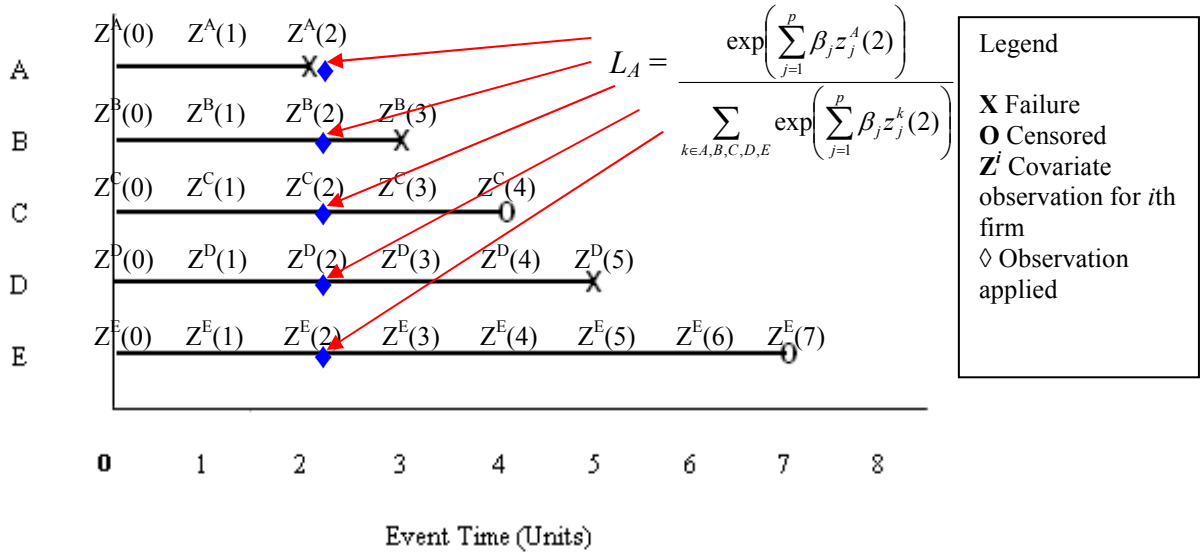
The Cox model with time-varying predictor variables can also be estimated using the partial likelihood function described earlier in Section 3.2.2. The estimation of the likelihood of a firm's failure with time-varying variables is essentially the same as that with time-invariant variables (the conventional Cox model), but it is required that the values of time-varying covariates of every firm in the risk set should be measured at each event time. The following equation is written for the ratio of firm  $i$ 's hazard to the hazards of all other firms in the risk set for each time ( $t$ ).

$$L_i = \frac{h_i(t | z(t))}{\sum_{k \in R_i(t)} h_k(t | z(t))} = \frac{h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^i(t)\right\}}{\sum_{k \in R_i(t)} h_0(t) \cdot \exp\left\{\sum_{j=1}^p \beta_j z_j^k(t)\right\}} = \frac{\exp\left\{\sum_{j=1}^p \beta_j z_j^i(t)\right\}}{\sum_{k \in R_i(t)} \exp\left\{\sum_{j=1}^p \beta_j z_j^k(t)\right\}}. \quad (5-3)$$

Figure 5-2 illustrates the likelihood function of Equation 5-3, where the respective covariate values of yearly observations of a firm's financial performance are updated at every incident of failure.

---

<sup>19</sup> When there are no time-varying variables the ratio of hazards for any two firms is constant over time and so traditionally the model has been known as Cox's proportional hazards model.



**Figure 5-2: Estimation of the Likelihood for the Failure of Firm A in a Cox Hazards Model with Time-Varying Covariates**

The figure illustrates the arrangement of the data in forming the likelihood function in a time-varying model. Observations of A through E are arranged in event time. The model inputs are updated at every incident of failure to reflect the observation's covariate values in the risk set at that particular time. Every time an event of failure is recorded, the vector of coefficients is re-estimated. The length of the line indicates the lifetime of the observation. An "X" marked at the end of the line denotes the event of failure, whereas an "O" marker indicates that the observation has been censored for reasons other than failure.

Given  $L_i$  (See Equation 5-3), the partial likelihood function with the incorporation of time-varying covariates can then be obtained by taking the product of the probabilities across all observed failures,  $m$ , so that:

$$PL = \prod_{i=1}^m L_i = \prod_{i=1}^m \left[ \frac{\exp\left(\sum_{j=1}^p \beta_j z_j^i(t)\right)}{\sum_{k \in R_i(t)} \exp\left(\sum_{j=1}^p \beta_j z_j^k(t)\right)} \right], \quad (5-4)$$

where  $i$  is the firm in the event of failure and  $k$  is the firm in the risk set at time  $t$ .

### **5.2.1 Difficulties in Practical Application of a Dynamic Cox Model to Financial Distress Prediction**

The Cox model using time-varying covariates is more efficient and dynamic in its use of data and is likely to produce less biased and more consistent estimates of financial distress probabilities (Shumway, 2001), but time-varying models have been difficult to put into practice. The major problems are attributable to breaches of the proportionality assumption and the requirement of having a complete set of covariate measures at every failure time.

As addressed earlier in Section 2.3.4.3, the problem with time-varying variables in the past has been in estimating the baseline hazard and consequently in forming forecasts. Previous studies (for example, Wheelock and Wilson, 1995; Kim et al., 1995) have not reported results of dynamic prediction since estimates of the baseline hazard are difficult to obtain when covariates in the model are time-varying.

In a time-invariant Cox proportional hazards model, the baseline hazard can be readily approximated based on the assumption that the hazards for each company are proportional. However, the mechanism of time-varying specification requires the covariate values of each observation of a company to be updated at every measurement; therefore, the parameter estimates are recomputed every time a failure event occurs. As a result, the hazard functions for all companies are not parallel anymore, nor are the relative hazards between companies proportional.

Likewise, due to technical difficulties, the current software (for example, SAS) is not capable of generating survival probabilities when the variables are changing with time.

The parameter estimation process implies that the time-varying covariate values of every firm in the risk set should be recorded and measured at each ‘failure time’. However, in practice, it is highly unlikely to have the complete covariate measures for all firms at every incident of failure, because the data set is likely to have missing observations, especially for financially distressed firms.

The contribution of this chapter is that a procedure is implemented to overcome these problems. The method used is based on a medical research paper by Chen et al. (2005). Their method uses the last observed information to impute any missing covariates values which resolves the second issue mentioned above. Chen et al. also implement a procedure to estimate baseline hazards when time-varying variables are used in the Cox hazards model. This is discussed in the next section.

### 5.2.2 Integrated Baseline Hazard

To generate survival probabilities at each time  $t$ , the baseline hazard function  $h_0(t)$  needs to be estimated. Chen et al. (2005) estimate the integrated baseline hazard function with time-dependent covariates based on Andersen (1992). The integrated baseline hazard function  $\hat{H}_0(t)$  can be estimated as follows.

$$\hat{H}_0(t) = \sum_{\tilde{T}_i \leq t} \frac{D_i}{\sum_{j \in R(\tilde{T}_i)} \exp(\hat{\beta}' \cdot z_j(\tilde{T}_i))}. \quad (5-5)$$

$D_i$  is the indicator for whether the firm  $i$  experiences the failure,  $\tilde{T}_i$  is the failure time for the  $i$ th firm,  $\hat{\beta}$  is the vector of estimated coefficients and  $z_j(\tilde{T}_i)$  is the value of the  $j$ th covariate at the failure time of the  $i$ th firm.

The integrated baseline hazard function  $H_0(t)$  can also be written as:

$$H_0(t) = \sum_{t_i \in t} [h_0(t_{m-1}) \times (t_m - t_{m-1})], \quad (5-6)$$

where  $H_0(t)$  is a step function, which is discontinuous at  $t_m$ . This allows the baseline hazard  $h_0(t)$  to be derived from the integrated hazard.

Using the estimated baseline hazard rate  $\hat{h}_0(t)$ , computed from equations 5-5 and 5-6, the estimated hazard rate of firm  $i$  with covariates  $z_i(t)$  at time  $t$  is derived as:

$$\hat{h}_i(t) = \hat{h}_0(t) \times \exp(\hat{\beta} \cdot z_i(t)). \quad (5-7)$$

### 5.2.3 Development of SAS Macro Program

Two SAS Macro programs for time-varying Cox hazards models are introduced in Chen et al. (2005). The first program is for parameter estimates on risk factors, deriving the baseline hazard and the prediction of survival on the basis of time-varying covariates. The second program validates the model's predictive accuracy using receiver operating characteristic (ROC) curves. The SAS Macro programs in Chen et al., with required modification, were used to provide forecasts for this thesis. The Appendices A and B contain the SAS programs written for this purpose.

## 5.3 Data and Evaluation Methods

As presented in Section 3.3 and 3.4 of this dissertation, a sample of Australian firms listed on the Australian Securities Exchange from 1995 to 2002 is used to

develop a dynamic Cox hazards model with time-varying variables. The accuracy of the model is assessed by generating survival probabilities for a holdout sample based on data from 2003 to 2006. Using firm-specific data, the model employs seven predictor variables measuring profitability, leverage (book and market), liquidity, cash flow, size, and growth opportunities. Receiver operating characteristic (ROC) curves and the Brier Score are used to evaluate the model's predictive power.

## **5.4 Results**

### **5.4.1 Model Estimation**

The dynamic Cox model for the hazard was estimated using the estimation sample (from 1995 to 2002) of 1,267 firms with 87 failure observations. The estimated parameters and the goodness of fit measure of the model are presented in Table 5-1. Panel A in Table 5-1 shows the total number of firms used in estimating the model parameters and the number of failed and censored firms. The resulting coefficient estimates of the model are shown in Panel B in Table 5-1 with their expected signs and their respective chi-square, and  $p$ -values (based on a chi-squared statistic for the significance of each coefficient).<sup>20</sup> Panel C provides an in-sample goodness of fit measure.

---

<sup>20</sup> The  $p$ -values are based on a Wald test-statistics as given by the squared ratio of the estimated coefficient to its estimated standard error.

**Table 5-1: Hazard Model Estimates**

Panel A shows the total number of firms, the number of failed firms and the number of censored (non-failed) firms and percentages of censored to the total number of firms in the estimation sample over the period of 1995 to 2002. Panel B reports the parameter estimates of the Cox hazards model with time-varying covariates,  $h_i(t | z(t)) = h_0(t) \cdot \exp\left\{\sum_{j=1}^P \beta_j z_j^i(t)\right\}$ . NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable. The goodness of fit of each model is presented in Panel C.

Panel A: Number of failed and censored firms in the estimation sample					
Total	Failed	Censored	Percent Censored		
1,267	87	1,180	93.13		
Panel B: Parameter estimates					
Variables	Expected sign	Coefficient	Std. Error	Chi-Square	p-Value
NI / TA	-	-0.03198	0.11799	0.0734	0.7864
WC / TA	-	-0.42753	0.23987	3.1767	0.0747
TL / TA	+	0.45184	0.07860	33.0472	<.0001
CF / TA	-	-0.52675	0.15608	11.3894	0.0007
MB	+	0.01182	0.02524	0.2193	0.6396
RSIZE	-	-0.10635	0.05841	3.3155	0.0686
MC / TL	-	-0.02247	0.00942	5.6934	0.0170
Panel C: Model Goodness of fit					
Criterion	Without Covariates		With Covariates		
-2 LOG L <sup>1</sup>	1176.910		1104.337		
Test	Chi-Square	DF	Pr > ChiSq		
Likelihood Ratio <sup>2</sup>	72.5728	7	< .0001		

<sup>1</sup> The term -2 LOG L is the logarithm of the maximum likelihood estimator for the model. It measures the goodness of fit of the presented model, and smaller values indicate a more desirable model.

<sup>2</sup> The likelihood ratio tests the null hypothesis that all coefficients except for the constant are zero. It is calculated as  $LR = 2(\ln L - \ln L_0)$ , where  $\ln L$  is the log likelihood of the estimated model and  $\ln L_0$  is the log likelihood of the restricted model only with a constant

Panel B of Table 5-1 shows that all of the variables have coefficients of the sign expected. Three of the variables are statistically significant at the 5% level and two at the 10% level. Of the significant variables, more operating liquidity, higher cash flow generating ability, larger relative size and more market value relative to debt, reduce the probability of failure as expected. A higher level of book leverage increases the probability of failure.

Table 5-2 shows the dynamic changes of risk scores and corresponding survival probabilities by time horizon. The time-varying risk scores can be calculated for each firm as  $\hat{\beta}z_i(t)$ . Following the approach of Chen et al. (2005),  $\hat{\beta}$  is a vector of estimated coefficients shown in Table 5-1 and  $z_i(t)$  is a vector of values of covariates for firm  $i$  at time  $t$ . For example, the risk score of Firm 1 at time 2 is estimated using the estimated coefficients from Table 5-1 and the values of seven predictor variables for firm 1 at the second year of the firm's lifetime.

The survival probabilities are calculated using the hazard from Equation 5-7 and taking the exponential of the negative integrated hazard. The estimation is as follows:

$$\hat{S}_i(t) = \exp\left[-\int \hat{h}_i(u)du\right]. \quad (5-8)$$

Panel A in Table 5-2 presents the resulting risk scores and survival probabilities for 10 randomly selected firms in the non-failed group and Panel B shows 10 firms in the failed group.<sup>21</sup> Comparing these survival probabilities for the

---

<sup>21</sup> Risk scores and survival probabilities are presented for only 20 firms in the study sample due to limited space.

failed firms with those of the surviving firms at the same time horizons (lifetime), the failing firms have lower probabilities. However, in most cases the differences are not great and the survival probabilities for the failed firms are generally high, with several above 0.9.

The explanation for the foregoing seems to lie in the interaction between the risk score and the baseline hazard. Since the incidence of failure in the estimation sample is small, the risk of failure for an average firm is small. Consequently, although the baseline hazard rises with time, it remains small. Thus, to obtain a small probability of survival requires a substantial scaling up of the baseline hazard by the risk score. It appears in this analysis that the risk scores for failed firms are not often large enough to achieve the required scaling up.

**Table 5-2: The Time-Varying Risk Scores and Survival Probabilities of 20 Firms Selected From Estimation Sample**

This table presents dynamic changes of risk scores (Score) and survival probabilities (P(S)) by time horizon using a time-varying Cox hazards model,  $h_i(t|z(t)) = h_0(t) \cdot \exp\left[\sum_{j=1}^p \beta_j z_j'(t)\right]$ , for 20 randomly selected firms over the period for which each firm was observed. The time-dependent risk score can be calculated for each firm as  $\hat{\beta}^* z_i(t)$ , where  $\hat{\beta}$  is a vector of estimated coefficients shown in Table 5-1 and  $z_i(t)$  is a vector of values of covariates for firm  $i$  at time  $t$ . The survival probabilities are calculated using  $\hat{h}_i(t) = \hat{h}_0(t) \times \exp(\hat{\beta} \cdot z_i(t))$  and  $\hat{S}_i(t) = \exp\left[-\int \hat{h}_i(u) du\right]$  and the estimated risk scores. Panel A shows the resulting risk scores and survival probabilities for 10 non-failed firms, and Panel B shows those for 10 failed firms.

Panel A: 10 Non-Failed Firms from Estimation Sample																				
Firm (i)	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Firm 7	Firm 8	Firm 9	Firm 10										
Lifetime (yrs)	3	4	5	6	6	6	7	7	7	8										
Status	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed	Non-failed										
Time horizon	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)
0	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	0.8028	0.9995	0.4400	0.9995	0.6588	0.9995	0.6066	0.9995	0.6523	0.9995	1.3563	0.9995	0.7058	0.9995	0.4239	0.9995	0.4048	0.9995	0.4048	0.9995
2	0.7545	0.9984	0.4351	0.9987	0.7027	0.9985	0.4902	0.9986	0.6080	0.9990	0.8000	0.9985	0.9727	0.9976	0.6949	0.9985	0.4559	0.9987	0.4308	0.9988
3	1.4228	0.9923	1.2470	0.9958	0.9608	0.9941	0.6850	0.9951	0.5995	0.9959	1.0386	0.9939	0.217	0.9941	0.6907	0.9948	-0.043	0.9959	0.292	0.9961
4			1.2470	0.9933	1.0440	0.9922	0.6362	0.9936	0.3294	0.9945	1.5352	0.9919	0.2149	0.9931	0.5620	0.9934	0.2558	0.9952	0.2837	0.9951
5			1.0440	0.9900		0.4957	0.9922	0.5185	0.9935	0.6586	0.9883	0.0675	0.9922	0.4963	0.9920	0.4934	0.9942	0.347	0.9941	
6						0.4957	0.9908	0.5185	0.9921	1.3838	0.9867	-0.665	0.9913	0.5995	0.9906	0.3288	0.9928	0.367	0.9929	
7												0.5837	0.9795	0.7558	0.9160	0.7962	0.8962	0.5261	0.9302	
8																			0.5217	0.8266

Panel B: 10 Failed Firms from Estimation Sample

Firm ( <i>t</i> )	Firm 11	Firm 12	Firm 13	Firm 14	Firm 15	Firm 16	Firm 17	Firm 18	Firm 19	Firm 20
Lifetime (yrs)	2	3	3	4	5	5	6	7	8	8
Status	Failed	Failed	Failed	Failed	Failed	Failed	Failed	Failed	Failed	Failed
Time horizon	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)	Score	P(S)
0	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	1.4936	0.9995	1.4474	0.9987	-3.898	0.9995	0.6032	0.9995	0.4369	0.9995
2	5.8930	0.7824	1.2389	0.9976	5.0650	0.9951	2.2117	0.9872	1.5925	0.9942
3		5.0935	0.9335	0.8861	5.0650	0.8861	0.8663	0.9806	4.0695	0.9907
4				0.8663	0.9788	4.0695	0.9461	1.0542	0.9906	2.0366
5					4.0695	0.9013	1.0542	0.9883	2.0732	0.9882
6						1.1564	0.9754	4.5098	0.9470	1.2462
7							4.5099	0.9006	2.7002	0.9847
8								6.2260	0.0500	5.0260
										0.3993
										0.0000
										1.5933
										0.9985
										1.3987
										0.9972
										1.3139
										0.9956
										1.3159
										0.9941
										1.6356
										0.9920
										2.2953
										0.9871
										2.6083
										0.9797

#### 5.4.2 Model Validation

This section presents the out-of-sample prediction results of the Cox hazards model with time-varying variables. In order to test the predictive power of the dynamic model proposed in this study, the performance of the dynamic model is compared to that of a conventional model. The widely used static technique of the logit model is chosen for this.<sup>22</sup> The prediction results of these two models are evaluated in both ordinal sense (ROC) and cardinal sense (Brier Score), as described in Section 3.4.

Panel A and Panel B in Table 5-3 present each model's predictive accuracy of the out-of-sample forecast based on ROC curves and the Brier Scores, respectively. The area under the ROC (AUROC) measures the discriminatory power of the model and the higher the AUROC the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel A examines predictive accuracy using the ROC curves and describes the AUROC for the holdout sample from 2003 to 2006. Panel B shows the Brier Score, which measures the deviation between the predicted probability of a failure event and the actual outcome of the event at the level of an individual company. The smaller the Brier Score the better the model. The naïve forecast is based on the proportion of defaults to the estimation sample.

For the dynamic Cox model, the predicted survival probabilities for out-of-sample forecast are computed in the same way as those of in-sample. That is, up until the event of failure in the holdout sample, the set of firms' annual observations as at

---

<sup>22</sup> See Section 2.3.2.3 to this dissertation for a brief description of logistic regression.

their financial year ends are entered into the model, with the values of covariates being updated as time passes. Thus, the survival probabilities at time  $t$  are based on data updated to time  $t$ . The consequence for failing firms is that the data used are the data last observed prior to failure. For example, a firm survives two years and fails after year three data is observed. The first year predicted survival probability based on the covariates observed at the end of year one in the holdout period will be evaluated at time horizon  $t = 1$ , and the second year forecast based on the covariates at the end of year two is assessed at  $t = 2$ . In year three, the third year forecast at  $t = 3$  is based on the data observed at that time. The firm is then withdrawn from the study because there are no data beyond year three.

Based on survival probabilities through time, the area under ROC curve and the Brier Score are computed. These metrics are then used to assess the predictive power of the model.

It can be problematic to compare prediction results of a time-varying dynamic Cox model to those of the static logit model. A particular effort has therefore been made so that the data for the logit model are aligned with those of the dynamic Cox model. That is, instead of having a set of data collected at a single point in time, all data across time are pooled and arranged according to event time. For example, if a firm has been at the risk set for three years from 2004 to 2006, each yearly observation of this firm would be listed in order and then the first year observation would be tagged as  $t = 1$ , the second year observation as  $t = 2$ , and so on. It is noted that any firm-year observations that belong to a failed (financially distressed) firm would be marked as failed observations. By doing this, a firm with three years of

observations would end up having three logit-based survival probabilities which change over time.

Overall, the dynamic model has stronger discriminatory power over the logit model across different time horizons (see Panel A in Table 5-3). Interestingly, the model's estimates do not deteriorate at longer horizons. This result is in direct contrast to prior bankruptcy studies, where predictive accuracy tends to decrease sharply as the time horizon lengthens. The results show that by  $t = 4$  the logit model has a level of discrimination that is slightly better than chance according to the ROC score. The result from Brier Score (see Panel B in Table 5-3) also verifies that the dynamic models perform better than the logit model.

**Table 5-3: Predictive Accuracy**

This table shows predictive accuracy of the out-of-sample forecast using the time-varying dynamic Cox hazards model and the conventional logit model. Panel A examines predictive accuracy using the ROC curves and describes the area under the ROC curves for a holdout sample for a period of 2003 to 2006. The AUROC measures the discriminatory power of the model. The higher the AUROC, the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel B shows the Brier Score, which measures the deviation between the predicted probability of a failure event and the actual outcome of the event at the level of an individual company. The smaller the Brier Score, the better the model. The naïve forecast is based on the proportion of defaults to the estimation sample.

Panel A: Predictive Accuracy of the Holdout Sample – Area Under the ROC Curve			
AUROC			
Time Horizon	Random Forecast	Dynamic Cox	Logit
t = 1	0.5	0.680	0.644
t = 2	0.5	0.709	0.669
t = 3	0.5	0.720	0.506
t = 4	0.5	0.701	0.572

Panel B: Predictive Accuracy of the Holdout Sample – Brier Score			
Brier Score			
Time Horizon	Naive Forecast	Dynamic Cox	Logit
t = 1	0.069	0.031	0.034
t = 2	0.070	0.024	0.028
t = 3	0.064	0.019	0.026
t = 4	0.053	0.005	0.012

### 5.4.3 Models with Industry Effect

It is evident that the likelihood of default varies across sectors and there have been some previous studies exploring the significance of including industry effects in financial distress prediction (Chava and Jarrow, 2004; Campbell et al., 2005). For example, mining and exploration companies are an important sector in Australian economy and some might argue that separate consideration should be given to mining companies due to the different nature of their operation and potentially different accounting numbers relative to manufacturing companies. A dummy variable for companies in the mining industry<sup>23</sup> was therefore included in the model. However, the results (not reported here) show that inclusion of the mining dummy did not improve the predictive ability of the model.

---

<sup>23</sup> Using the Global Industry Classification Standard (GICS) structure, companies under the GICS Metals & Mining Industry (GICS Code: 151040) are classified as “mining and exploration companies”, whose industry dummy variables are coded as “1”.

## 5.5 Conclusions and Suggestions for Future Research

Problems with time-varying predictor variables and estimating baseline hazards have been major obstacles in the application of survival analysis to multiple-period bankruptcy data. This study has taken a step towards solving these problems by applying the time-varying Cox hazards model to Australian financial distress prediction. Seven covariates are used, whose values are updated on a yearly basis from 1995 to 2006. The attractive feature of time-varying survival modelling is that it allows for dynamic changes of a firm's risk levels and its corresponding survival probabilities through time.

As the interaction between the financial distress risk and firm-specific accounting-based and market-based ratios is explored, the result obtained suggests that firms with less operating liquidity, higher book leverage, less cash flow generating ability, smaller size and less market value relative to debt are more likely to fail, which is partly in line with the results found in Shumway (2001). The combination of a dynamic model and the dynamic updating of input data results in the model maintaining predictive accuracy as the firms are observed to evolve with time. The time-varying Cox hazards model is shown to outperform the logit model at each forecast date in the period which the firms are examined.

However, the predictive power of the model is modest and there is scope for considerable improvement. The current model does not allow for changes in macroeconomic variables, so a possible extension would be to introduce such variables, or to alternatively control the effect of such variables by estimating the

model in calendar time rather than event time. There may also be problems regarding survival bias in the availability of data and this may be more prevalent in the early years of the study.

# **CHAPTER 6: THE DYNAMIC PREDICTION OF COMPANY FAILURE – THE INFLUENCE OF THE ECONOMY AND NON- LINEARITY**

## **6.1 Introduction**

During the past two decades there has been a growing recognition of the need to investigate how corporate failures (or credit risk scores) are influenced by macroeconomic fluctuations (Kane, Richardson, and Graybeal, 1996; Richardson, Kane and Lobingier, 1998; Kent and D’Arcy, 2001; Partington, Russel, Stevenson and Torbey, 2001; Liu, 2004; Rösch and Scheule, 2005; Pesaran, Schuermann, Treutler and Weiner, 2006; Carling, Jacobson, Linde and Roszbach, 2007; Wong, Partington, Stevenson and Torbey, 2007; Oxelheim and Wihlborg, 2008; Bellotti and Crook, 2009; Bonfim, 2009; Cole and Wu, 2009). As discussed earlier in Section 2.4.2, the role of macroeconomic indicators in predicting financial distress has been subject to debate. However, more recent empirical studies have found significant improvement in model performance from the inclusion of economy-wide variables (Pesaran et al., 2006; Carling et al., 2007; Nam et al., 2008; Bellotti and Crook, 2009; Bonfim, 2009).

In this study, the basic time-varying model as developed in Section 5.2 (hereafter referred to as the base model or *Model 1*) is extended to capture macroeconomic changes over time. The extended model has both time-varying firm-

specific covariates and time-varying macroeconomic covariates, which makes it possible to track changes both in the firm and economy through time.

In addition to examining the impact of economic conditions on company failures, this chapter also considers the possible non-linear relation between predictor variables and the event of failure. The risk of corporate failure is not necessarily linearly related to predictor variables. In prior financial distress studies, little attention has been paid to investigating non-linear effects of firm characteristics on the risk of firm failure. A recent exception is Chan, Faff, Gharghori and Lajbcygier (2008), who used a non-linear technique called generalised additive models (GAMs). The disadvantages of this technique are its computational complexity and its black-box nature. This study uses a simple non-parametric data transformation of predictor variables based on default rates, and incorporates the non-linear relation between predictor variables and the failure risk of a firm into the time-varying Cox hazards model. The technique used was suggested by Loffler and Posch (2007) and the proposed approach is much simpler, more transparent and less computationally demanding than Chan et al. (2008).

The remainder of this chapter proceeds as follows. The next section provides an empirical discussion of why macroeconomic risk indicators are needed and how they are incorporated into the model. Section 6.3 discusses the non-linear approach to modelling failure. Section 6.4 describes the data and provides descriptive statistics, while Section 6.5 analyses the predictive accuracy of the estimated models. The final section concludes the chapter and gives suggestions for future research.

## **6.2 Macroeconomic Risk Factors and the Prediction of Company**

### **Failure**

#### **6.2.1 Motivation**

The motivation of this study is twofold. First, as discussed in Section 3.2.1, there is a difference between arranging the data in terms of calendar time and event time. Panel A in Figure 6-1 shows the data arrangement on the calendar time which reflects the real-world phenomenon. Companies can enter the study at different times. However, Panel B shows the data arrangement when the model is estimated. All firm observations enter the study at event time 0.

Problems arise from the mismatch of calendar dates when the risk set is arranged in event time. For example, in an event time model, the first yearly observation for a company A could be in June 1997, while the first yearly observation for Company B could be in June 1999. In this case, the correct value of the macroeconomic covariates at first year observation must differ between companies. For this end, macroeconomic variables are added to the model to correct the problem of mismatch in timing. In this study, time-varying macroeconomic covariates are used to capture macroeconomic changes through time.

Second, the information in the macroeconomic variables is likely to be incorporated into the baseline hazard in *Model 1* in an ad-hoc manner. This is because any effect that is not explicitly modelled in the vector of covariates becomes subsumed into the baseline hazard function. This raises the possibility of model

misspecification.<sup>24</sup> As pointed out by Hamerle et al. (2003), Rosch and Scheule (2004) and Rosch and Scheule (2005), unobservable risk factors are likely to induce uncertainties into the forecasts of default distributions.

Therefore, including macroeconomic variables in the model aids better controls for systemic risk factors by taking out of the baseline the latent effects of broad economic conditions and placing them directly into the model.<sup>25</sup> In previous research, Rosch and Scheule (2005) demonstrated in their multi-factor model that default rates fluctuate cyclically and part of this is attributed to systematic risk indicators. It is expected that identifying these risk factors and incorporating them into the base model reduces the chance of model misspecification and may enhance model performance.

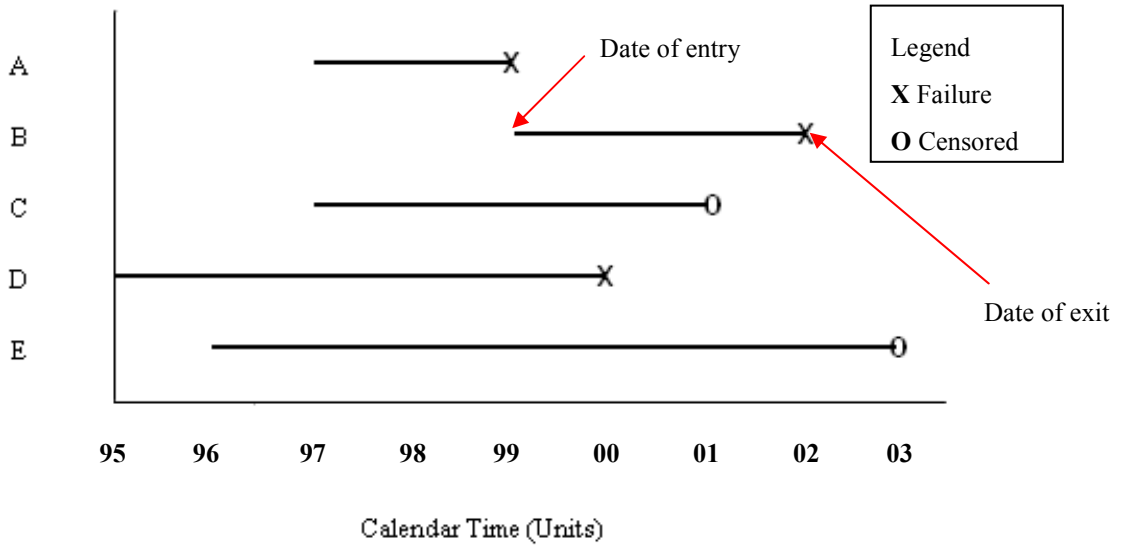
However, it should be noted that having macroeconomic variables as predictors is not the major focus of this study; rather, they are included as control variables. The main reason to include controls for the state of the economy is so that firm observations, arranged in event time, are able to be assessed according to their corresponding states of the economy.

---

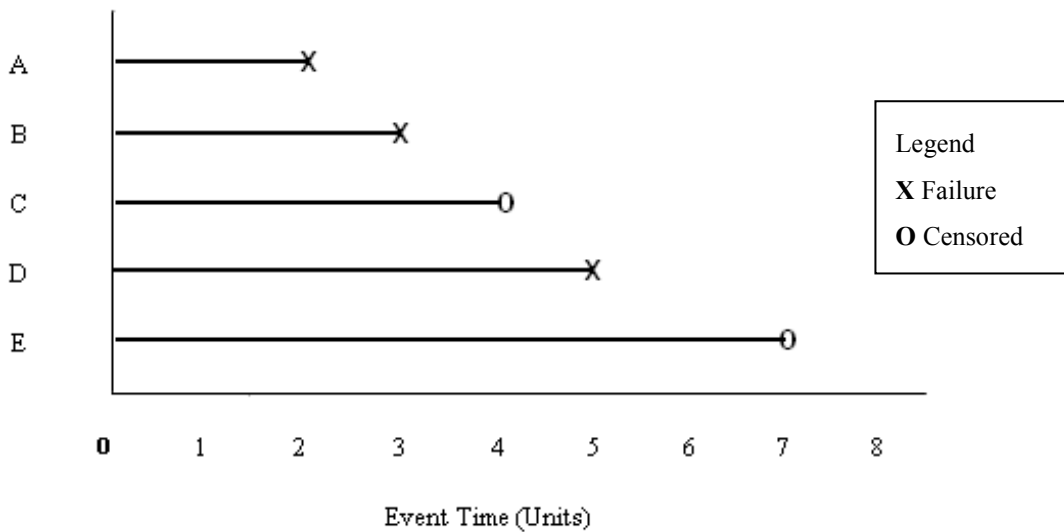
<sup>24</sup> Model misspecification in this context refers to a model that yields biased and more inconsistent coefficients and standard errors.

<sup>25</sup> Hillegeist et al. (2004) also suggest that the time-varying hazard rate should be measured by including the system-level variables, such as macroeconomic factors, and incorporated into the bankruptcy model so as to reduce the likelihood of biased and inconsistent coefficients and standard errors.

**Panel A: Arrangement of Firms in the Risk Set according to Calendar Time**



**Panel B: Arrangement of Firms in the Risk Set according to Event Time**



**Figure 6-1: Calendar Time versus Event Time**

The figure above presents a graphical demonstration of the difference between arranging the data in terms of “calendar time” and “event time”. Panel A illustrates observations of A to E arranged in calendar time while Panel B does so in event time. It is noted that observations can enter the study at different times in Panel A; however, every observation enters the study at event time 0 in Panel B. The length of the line indicates the lifetime of the observation. An “X” at the end of the line denotes the event of failure, whereas an “O” indicates that the observation has been censored for reasons other than failure.

## **6.2.2 A Time-Varying Cox Hazards Model with Macroeconomic Control**

### **Variables**

Four leading indicators of broad economic conditions are considered in this study: the ASX All Ordinaries Index, yield spread, consumer confidence index and the consumer price index (inflation effect). Given that every firm-year observation in the existing sample is complemented by a set of macroeconomic data measured as at the date of a firm's financial year end, each value of macroeconomic covariates is a time-varying variable. The model now has 11 time-varying covariates, including seven idiosyncratic firm-specific covariates and four systematic macroeconomic covariates, which will be referred to as *Model 2* hereafter.

## **6.3 Non-Linear Relation between Company Failure and Predictor**

### **Variables**

#### **6.3.1 Why a Non-Linear Approach to Failure Risk Modelling?**

For certain accounting ratios, it is reasonable to expect a non-linear relation with failure risk. For example, a company may fail if it has insufficient liquidity to pay its bills. However, a company may also fail if it has too many current assets, such as investments that are not selling. The company can fail because it has to finance these assets even when they are not generating cash flow.<sup>26</sup> So both too much liquidity

---

<sup>26</sup> “It would seem that a company with a higher liquid ratio is in a healthier position than one with a lower ratio. However, this is relative; the real question is whether a company has access to sufficient liquidity to meet its forecast need under a pessimistic business scenario. Too much liquidity is not a good performance indicator, as there is a cost in maintaining a high level of liquidity: the return received on liquid assets is generally lower.” (Viney 2003, p.218)

and too little liquidity can increase the risk of financial distress. This is a non-linear relation.

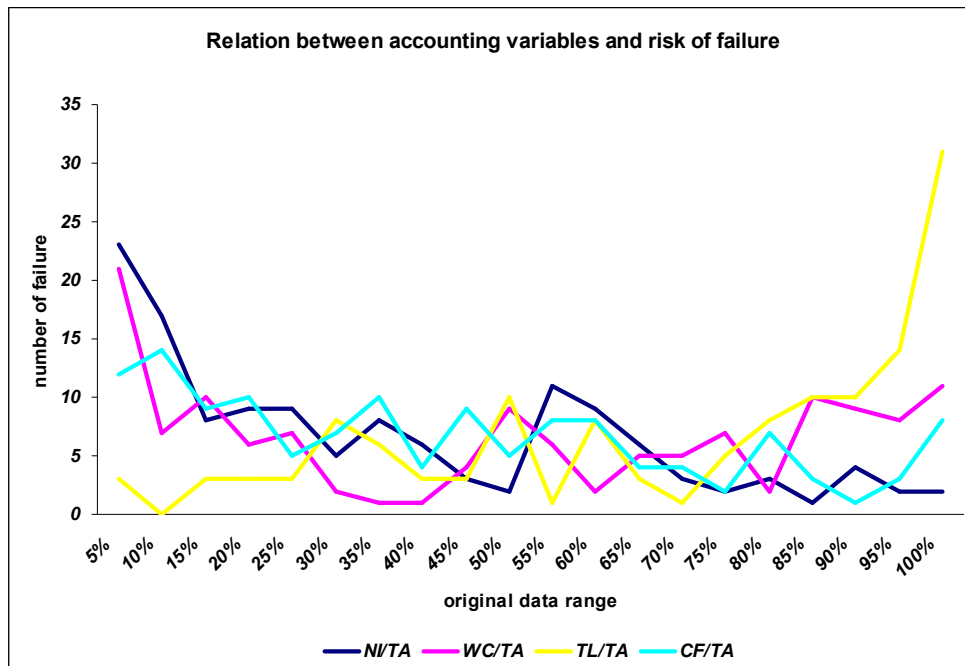
Threshold effects can also be present. For example, if a company is massively profitable it is likely to be safe and if it is moderately profitable it is still likely to be safe. So it only matters if the profit drops below some threshold where the company has low profits, or it is not profitable at all.

The univariate analysis presented in Figure 6-2 illustrates non-linearities between failure risk and predictor variables. It can be observed that there is marked U-shape relation between WC/TA, MB and failure risk.

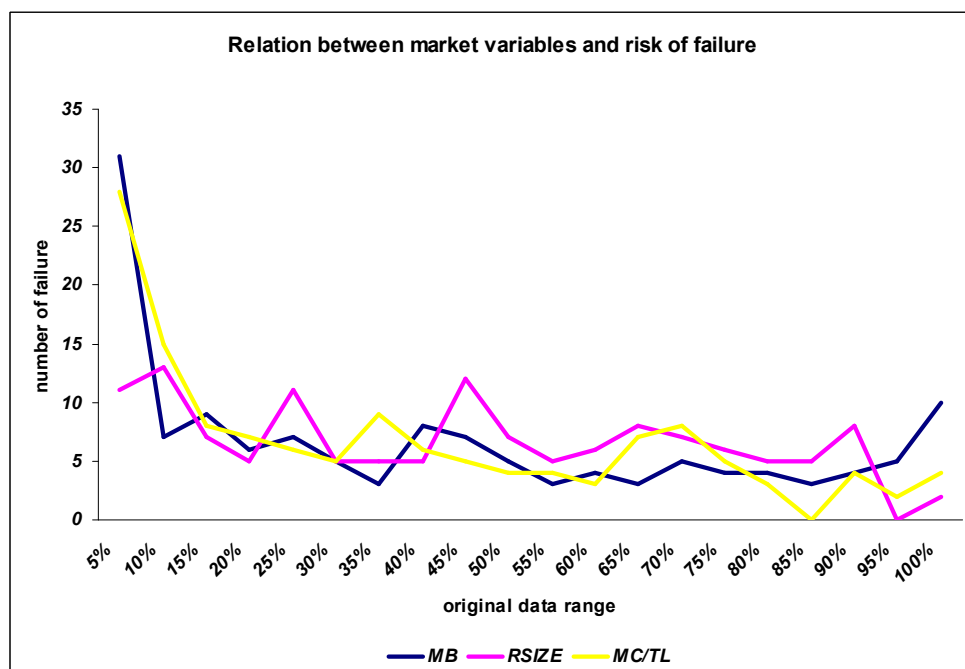
In Figure 6-2, the original data range is divided up into 20 classes of five percentiles for each variable ratio. The number of company failures (defaults) in each class is counted and plotted on the graph. For example, in Panel A, the pink line presents how the default rate changes as the liquidity ratio changes. Very low liquidity causes high default rates and the default decreases as the liquidity increases then goes up again when the liquidity is very high. The relation between leverage and defaults (the yellow line) suggests a threshold effect.

In general, none of the accounting variables show a linear relation with the default risk in Panel A and a similar conclusion applies to the market-based variables in Panel B of Figure 6-2. The MB ratio and market leverage (MC/TL) have threshold effects, so that once the ratios drop below some threshold, the risk of failure increases substantially.

**Panel A: Relation between Accounting-Based Variables and the Risk of Default**



**Panel B: Relation between Market-Based Variables and the Risk of Default**



**Figure 6-2: Non-Linear Relation between Predictor Variables and the Risk of Default**

The figure examines the univariate relationship between default risk and predictor variables. Panel A shows how the default risk varies as the accounting ratio changes and Panel B presents the relation between the default risk and the market-based variables.

### **6.3.2 A Time-Varying Cox Hazards Model with Non-Parametric Data**

#### **Transformation Based on Failure Rates**

The original data range is divided up into 20 classes of five percentiles each and the range of observations is noted in each class. The incidents of defaults and the number of observations are then counted respectively in each class and the default rate is calculated for that class. Instead of using the original values of the variables, they are recorded to the default rates that match the range that the original values were assigned to. In this way the original variable is transformed to a default rate. This embeds the non-linear relation between predictor variables and the failure risk of a firm into the Cox hazards model.

The non-parametric transformation is first applied to firm-specific variables only and is used in *Model 3*. The macroeconomic variables are also transformed and included in *Model 4*, so that the performance of *Model 3* and *Model 4* can be assessed vis-à-vis *Model 1* and *Model 2*. In all cases the estimated coefficients are expected to be positive in *Model 3* and *Model 4* because the variables are transformed to default rates and a higher default rate increases the hazard of failure.

It is noted that this approach may give rise to a data mining problem: overfitting. As a data-driven transformation is conducted in building the model, the model relies heavily on the available sample data. This can cause lack of generalisability resulting in a decline in the out-of-sample prediction accuracy of the model (Richardson et al., 1998). This issue is examined empirically with out-of-sample predictions presented in Section 6.5.2.

## **6.4 Data and Evaluation Method**

The sample of firms is the same as that introduced in Section 3.3 (Australian firms listed on the Australian Securities Exchange from 1995 to 2006). As presented in Section 3.3, the firm-specific variables used in *Model 1* and *Model 3* measure profitability, leverage (book and market), liquidity, cash flow, size, and growth opportunities. Details of macroeconomic variables used in *Model 2* and *Model 4* are provided in the following section. For the purpose of model validation, receiver operating characteristic (ROC) curves and Brier Score are used to evaluate the model's predictive power.

### **6.4.1 Macroeconomic Variables**

For the purpose of capturing economy-wide changes through time, a set of macroeconomic covariates are introduced as control variables in this study. As shown in Table 6-1, leading indicators found in previous financial distress studies at the macroeconomic level include yield spread, default spread, return on the market index, consumer confidence index, consumer price index (inflation) and unemployment rates (Partington et al., 2001; Liu, 2004; Rosch and Scheule, 2005; Wong et al., 2007; Bellotti and Crook 2009; Bonfim 2009). Macroeconomic data are obtained from two sources: the annualised return on All Ordinaries Index from SIRCA and other macroeconomic data from the Reserve Bank of Australia (RBA) website. The data cover the entire sample period from 1995 to 2006.

**Table 6-1: Macroeconomic Variables Used in Previous Financial Distress Studies**

This table shows leading economic indicators used in a number of previous financial distress studies. Six macroeconomic variables are initially considered but two of the following variables, default spread and unemployment rate, are excluded in the model due to insufficient data on corporate bond yield and multicollinearity, respectively. Data are obtained from SIRCA and RBA website during the period between 1995 and 2006. AOI is the annualised price return of All Ordinaries Index. DEFAULT SPREAD is the difference between the Treasury Bond Yield and the BAA Corporate Bond Yield (Moody's). YIELD SPREAD is 10-year Commonwealth Government Treasury Bond yields less 90-day Bank Accepted Bills (BAB) yields. CCI is the annualised rate of changes (percentage changes) in the Consumer Confidence Index. CPI is the annualised rate of changes in the Consumer Price Index indicating the inflation effect. UNEMP is the unemployment rate.

Description	Ratio / Variable	Abbreviation	Source	Frequency	Included in the present study
Return on AOI	$(r_{m,t} / r_{m,t-1}) - 1$	AOI	Rosch & Scheule (2005) Bonfim (2009)	Annual	Yes
Default Spread	Treasury Bond yield – BAA Corporate Bond yield (Moody's)	DEFAULT SPREAD	Partington et al. (2001) Wong et al. (2007)	Annual	No
Yield Spread	10 Year Government Bond yield – 90 day Bank Accepted Bills	YIELD SPREAD	Partington et al. (2001) Rosch & Scheule (2005) Wong et al. (2007)	Annual	Yes
Rate of Change in Consumer Confidence Index	$(CCI_t / CCI_{t-1}) - 1$	CCI	Rosch & Scheule (2005) Bellotti & Crook (2009)	Annual	Yes
Rate of Change in Consumer Price Index	$(CPI_t / CPI_{t-1}) - 1$	CPI	Liu (2004) Bonfim (2009)	Annual	Yes
Unemployment rate	Unemployment rate	UNEMP	Bellotti & Crook (2009)	Annual	No

Default spread is not included in this study due to a lack of data on corporate bond yields. The unemployment rate is also excluded because of potential problems with multicollinearity (see Table 6-3).

The yield spread, as given by the Australian Government Bond yield less Australian Treasury Notes yield, captures business cycle effects. Widening yield spreads, particularly when driven by cuts to short-term interest rates, are often associated with deteriorating economic conditions and hence increased default risk. To construct the yield spread, monthly yields on 10-year Commonwealth Government Treasury Bonds and monthly yields on 90-day Bank Accepted Bills (BAB) are collected from the RBA website. The yields on 90-day BAB are used as short-term securities because the Commonwealth Government has suspended issues of three-month Treasury Notes from December 2002.<sup>27</sup>

The role of yield spread depends on what is driving the change in spread. First, if the spread is widening because of cuts to short-term interest rates as Central Banks try to stimulate a depressed economy, then default risk is likely to rise in the short term. Alternatively, yield spread can be used to reflect future economic conditions. Ford and Taylor (2005) explain the relationship between the yield spread and future economic growth as follows: “When the economy is strong, there will be an expectation of higher average short-term interest rates in the future. Expectations of higher average short-term rates will lead to bond yields being higher than present short-term rates and thus to a higher yield spread. Conversely, when the economy is weak there will be an expectation of lower average short-term interest rates in the

---

<sup>27</sup> Ford and Taylor (2005) also use 10-year Government Bond yield and 90-day Bank Accepted Bills to generate the yield spread and Karfakis and Phipps (1996) use 90-day Bank Accepted Bills for the proxy of Australian short-term government securities.

future, leading to a lower (and possibly negative) yield spread” (Ford and Taylor 2005, p.114). These two arguments are antithetical. In this study, based on the first argument above and the empirical results of Rosch and Scheule (2005), it is hypothesised that a widening yield spread will increase the risk of financial distress.

The return on the market index is expected to have a negative impact on the failure risk. When the stock market is on the rise, it generally reflects an improvement in companies’ financial condition, resulting in lower failure rates.

The Consumer Confidence Index (CCI) is a leading indicator of economic activity. A negative coefficient is expected on the CCI; thus, when the CCI goes up, the chances of recessions go down.

Inflation, measured by the change in price from the Consumer Price Index (CPI), is usually strong during economic expansions. However, it should be noted that there are two effects. One is the inflation variable acting as an indicator variable for the economy, and the other is the impact of inflation on the individual firm, which may not have been identified in the accounting covariates. Strong inflation implies the economy is going well, but in the end, inflation is bad for economic activity. If inflation keeps increasing, the real economy starts to deteriorate. Inflation is also associated with an increase in interest rates, and this puts more pressure on business cash flows. Wadhvani’s (1986) analysis shows that higher inflation leads to higher bankruptcy rates.

A summary of statistics in macroeconomic variables for all firm-year observations of the entire sample are presented in Table 6-2. Percentage changes of

macroeconomic variables are expressed in the form of decimal fractions to be consistent with the scale used for firm-specific data.

**Table 6-2: Summary Statistics of Macroeconomic Variables**

This table shows descriptive statistics of macroeconomic variables used in this study over the period of 1995 to 2006. Data are obtained from SIRCA and RBA website. AOI is the annualised price return of All Ordinaries Index. YIELD SPREAD is 10-year Commonwealth Government Treasury Bond yields less 90-day Bank Accepted Bills (BAB) yields. CCI is the annualised rate of changes (percentage changes) in the Consumer Confidence Index. CPI is the annualised rate of changes in the Consumer Price Index indicating the inflation effect.

Variables	Mean	Median	Std. Dev.	Minimum	Maximum
AOI	0.0955	0.1012	0.0874	-0.0862	0.2994
YIELD SPREAD	0.0093	0.0107	0.0063	-0.0074	0.0195
CCI	-0.0005	0.0143	0.0990	-0.1910	0.3227
CPI	0.0280	0.0284	0.0185	-0.0033	0.0608

Correlation matrices of the five leading indicators of economic conditions, initially considered for this study, are presented in Table 6-3. The Pearson Product-Moment correlations are examined. All correlations presented in Table 6-3 are statistically significant at the 1% level except for the correlation between CCI and CPI (where  $p$ -value = 0.7665). The correlation between yield spread and unemployment rate is the highest in the table, followed by the correlation between unemployment and the return on the index and the correlation between yield spread and the return on the index. Due to concerns about multicollinearity the unemployment rate is not included in the model.

**Table 6-3: Correlation Matrix**

This table presents the Pearson Product-Moment correlations. Pearson correlation statistics are computed from observations with non-missing values for each pair of macroeconomic variables. All correlations are significant at the 1% level (two-sided test) except for the correlation between CCI and CPI (where  $p$ -value = 0.7665). Data have been obtained from SIRCA and RBA website during the period between 1995 and 2006. AOI is the annualised price return of the All Ordinaries Index. YIELD SPREAD is 10-year Commonwealth Government Treasury Bond yields less 90-day Bank Accepted Bills (BAB) yields. CCI is the annualised rate of changes (percentage changes) in the Consumer Confidence Index. CPI is the annualised rate of changes in the Consumer Price Index indicating the inflation effect. UNEMP is the unemployment rate. Correlation matrices of the five covariates are constructed for the entire sample period.

Variables	AOI	YIELD SPREAD	CCI	CPI	UNEMP
AOI		0.3769	-0.0434	-0.2589	0.4249
YIELD SPREAD			0.2960	-0.1091	0.5120
CCI				-0.0036	-0.275
CPI					-0.3019
UNEMP					

## 6.5 Results

### 6.5.1 Model Estimation

The time-varying Cox hazards model with firm-specific variables (*Model 1*), the extended model with macroeconomic control variables (*Model 2*) and the models with non-parametric transformation based on default rates (*Model 3* and *Model 4*) have been estimated using the estimation sample (from 1995 to 2002) of 1,267 listed Australian firms, with 87 failure observations.

The estimated parameters and the goodness of fit measure of the models are presented in Table 6-4. Panel A in Table 6-4 shows the total number of firms used in estimating model parameters, and each number of failed and censored firms. The resulting coefficient estimates of the four models are shown in Panel B in Table 6-4, with their expected signs and their respective  $p$ -values (based on a chi-squared

statistic for the significance of each coefficient).<sup>28</sup> Panel C provides an in-sample goodness of fit measure.

In the third column of Panel B, it is shown that all of the variables in *Model 1* have coefficients of the sign expected and five of the variables are statistically significant in explaining failure risk, as previously discussed in Section 5.4.1.

Moving to the next column (*Model 2*), the parameter estimates of all firm-specific variables remain unchanged from *Model 1* in terms of sign, and almost consistent in terms of magnitude and statistical significance. The macroeconomic variables, return on market index, inflation and consumer confidence index are insignificant. Yield spread is the only significant macroeconomic covariate.

The negative coefficient on yield spread is contrary to expectations. It indicates that a higher yield spread results in a decrease in the risk of financial distress. Reflecting upon the effect of the yield spread on the failure risk, it is suspected that the result arises from the potential opposite signs of the current and future effects. For instance, taking the current case in Australia, the yield spread has widened as the government has cut short-term rates in an attempt to stimulate the economy, which is projected to recover in a year or two. Therefore, wider yield spread reflects poor current economic conditions and improving future economic growth. This suggests that the wider yield spread is associated with an increased failure risk in the present but a reduced risk in the future.

---

<sup>28</sup> The p-values are based on a Wald test-statistics as given by the squared ratio of the estimated coefficient to its estimated standard error.

The second-last column (*Model 3*) has four statistically significant variables in common with *Model 1*. As was the case in *Model 1*, book leverage, cash flow generating ability, size and market value relative to debt are significant. However, operating liquidity is driven to insignificance and instead profitability is found to be a significant variable. In the last column (*Model 4*) where all transformed firm-specific and macroeconomic variables are included, yield spread becomes insignificant whereas other macroeconomic variables become significant. All significant coefficients in *Model 3 and Model 4* have the expected positive signs, except for CPI in *Model 4*. The likelihood ratios in Panel C indicate that the model fit is progressively better in moving from *Model 1* through to *Model 4*. Whether this results in better predictive performance is investigated in the next section.

**Table 6-4: Parameter Estimates and Model Fit Summary for Model 1, 2, 3 and 4**

Panel A shows the total number of firms, the number of failed firms and the number of censored (non-failed) firms and percentages of censored to the total number of firms in the estimation sample over the period of 1995 to 2002. Panel B reports the parameter estimates of four models: the time-varying Cox hazards model with firm-specific variables (*Model 1*), the extended model with macroeconomic control variables (*Model 2*) and the models with non-parametric transformation based on default rates (*Model 3* and *Model 4*). NI/TA is the firm's net income divided by its total assets; WC/TA is the firm's working capital divided by its total assets; TL/TA is the ratio of the firm's total liabilities to its total assets; CF/TA is the ratio of the firm's net operating cash flow to its total assets; MB is the market-to-book ratio measured as the firm's market capitalisation to its total book equity; RSIZE is the firm's relative size measured as the natural logarithm of the ratio of each firm's market capitalisation to that of the ASX All Ordinaries Index; MC/TL is the firm's market capitalisation divided by its total liabilities. AOI is the annualised price return of All Ordinaries Index; YIELD SPREAD is 10-year Commonwealth Government Treasury Bond yields less 90-day Bank Accepted Bills (BAB) yields; CCI is the annualised rate of changes (percentage changes) in the Consumer Confidence Index; CPI is the annualised rate of changes in the Consumer Price Index indicating the inflation effect. A positive coefficient on a particular variable implies that the hazard rate is increasing in that variable. Parameter estimates are given first followed by *p-values*. The chi-square of the likelihood ratio test for the model fit is reported in Panel C. The last 11 variables suffixed “\_d” are the firm-specific and macroeconomic variables whose values have been replaced by the default rates. \*\*\* significant at 1%, \*\* significant at 5%, \* significant at 10%

Panel A: Number of failed and censored firms in the estimation sample					
	Total	Failed	Censored	Percent Censored	
	1,267	87	1,180	93.13	
Panel B: Parameter estimates					
Variables	Expected Sign	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
NI / TA	-	-0.0319	-0.0854		
WC / TA	-	-0.4275*	-0.4090*		
TL / TA	+	0.4518***	0.4621***		
CF / TA	-	-0.5268***	-0.4870***		
MB	+	0.0118	0.0118		
RSIZE	-	-0.1064*	-0.1170**		
MC / TL	-	-0.0225**	-0.0226**		
AOI	-		2.3202		
YIELD SPREAD	+		-71.1503**		
CCI	-		-0.7718		
CPI	(?)		-0.3049		
NI / TA_d	+			25.0725**	24.8284**
WC / Ta_d	+			12.5756	16.3893
TL / Ta_d	+			23.1360***	23.0240***
CF / Ta_d	+			45.1592**	45.9273**
MB_d	+			-2.4153	-2.9249
RSIZE_d	+			35.3105*	44.0214**
MC / TL_d	+			33.8051***	33.1724***
AOI_d	+				120.1746***
YIELD SPREAD_d	+				-7.3239
CCI_d	+				101.5115***
CPI_d	+				-77.8926**

Panel C: Model Goodness of fit					
	Without Covariates	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
-2 LOG L	1176.910	1104.337	1093.277	1076.892	1054.944
Likelihood Ratio		72.5728***	83.6336***	100.0184***	121.9658***
Degrees of Freedom		7	11	7	11

### 6.5.2 Model Validation and Implication of Modelling with Macroeconomic Covariates and with a Non-Linear Approach

This section presents the out-of-sample prediction results of each of four models and compares the performance of one model against the other. While the focus is to examine whether the incorporation of macroeconomic indicators and the adoption of a non-linear approach can play an important role in improving the model's predictive power, all four dynamic Cox models are compared to conventional static models. Four versions of the logit model are set up to correspond to the time-varying Cox hazards models (*Model 1*, *Model 2*, *Model 3* and *Model 4*). The prediction results of these eight models are evaluated in both an ordinal sense (ROC) and a cardinal sense (Brier Score), as described in Section 3.4.

Results of Panel A in Table 6-5 show that the dynamic model has stronger discriminatory power over the logit model across different models and different time horizons, with one exception in which the logit model with transformed firm-specific variables (the logit model under *Model 3*) at time horizon  $t = 4$  shows the highest accuracy (AUROC = 0.848). Similar results can be seen in the Brier Scores of Panel B in Table 6-5. In contrast to the logit model, which shows considerable fluctuation in

predictive accuracy across different models and different time horizons, the prediction accuracy of the dynamic model is less volatile. Indeed, the Brier Scores are identical in the first-year forecast across all four models.

It is notable that allowing for non-linearity between predictor variables and the risk of financial distress substantively enhances the model's discriminatory power as shown in Panel A of Table 6-5. The superior predictive accuracy of *Model 3* (AUROC about 80%) against that of *Model 1* (AUROC about 70%) suggests that researchers should consider a non-linear approach as a further step in developing bankruptcy prediction models that have higher discriminatory power.

In contrast to the improvement in the AUROC statistics, the Brier Scores show no consistent improvement and in some cases the results are slightly worse after allowing for non-linearity. So it seems that there has been no substantive improvement in the accuracy of estimated probabilities. Possibly this might be improved by some recalibration of the models.

As for the effect of macroeconomic covariates, contrary to expectations, models that control the state of the economy (*Model 2* and *Model 4*) do not have higher predictive power than the same failure prediction models which have no economy-wide indicators (*Model 1* and *Model 3*), as shown in Table 6-5. At the outset, it is suggested that the information on economy-wide conditions should be confounded in the baseline hazard, but the result provides no evidence of an effect on predictive accuracy. Three potential reasons for this result can be suggested. First, it is possible that the firm-specific variables already embed the impact of the

macroeconomic variables on the firms' financial performance. If so, the macroeconomic variables would add relatively little information to the model.

A second reason may be the limited extent of the economic data. The estimation model only has eight years of data and there may simply be insufficient variation in that time series data to reliably estimate the effect of the macroeconomy on financial distress. A similar result has been recently found in Cole and Wu (2009).

The third potential reason for the observed result is that the effect of macroeconomic variables may act with a lag, and thus the figure as at the firm's financial year end may not be the required measurement of macroeconomic conditions. It may be worthwhile for researchers to investigate whether an exponentially weighted moving average for macroeconomic conditions can improve the predictive power of financial distress models.

**Table 6-5: Predictive Accuracy**

This table shows predictive accuracy of the out-of-sample forecast using four models. Panel A examines predictive accuracy using the ROC curves and describes the area under the ROC curves for a holdout sample for a period of 2003 to 2006. The AUROC measures the discriminatory power of the model. The higher the AUROC, the better the model. Predictions made at random have an AUROC of 0.5 and models that do not beat this benchmark have no predictive power. Panel B shows the Brier Score, which measures the deviation between the predicted probability of a failure event and the actual outcome of the event at the level of an individual company. The smaller the Brier Score, the better the model. The naive forecast is based on the proportion of defaults to the estimation sample.

Panel A: Predictive Accuracy of the Holdout Sample – Area Under the ROC Curve													
		<i>Model 1</i>			<i>Model 2</i>			<i>Model 3</i>			<i>Model 4</i>		
Time Horizon	Random Forecast	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit
t = 1	0.5	0.680	0.644	0.683	0.488	0.784	0.684	0.761	0.612	0.784	0.684	0.761	0.612
t = 2	0.5	0.709	0.669	0.704	0.666	0.787	0.696	0.775	0.696	0.787	0.696	0.775	0.696
t = 3	0.5	0.720	0.506	0.678	0.646	0.819	0.771	0.757	0.726	0.819	0.771	0.757	0.726
t = 4	0.5	0.701	0.572	0.584	0.536	0.814	0.848	0.661	0.487	0.814	0.848	0.661	0.487

Panel B: Predictive Accuracy of the Holdout Sample – Brier Score													
		<i>Model 1</i>			<i>Model 2</i>			<i>Model 3</i>			<i>Model 4</i>		
Time Horizon	Naive Forecast	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit	Dynamic Cox	Logit
t = 1	0.069	0.031	0.034	0.031	0.211	0.031	0.033	0.031	0.079	0.031	0.033	0.031	0.079
t = 2	0.070	0.024	0.028	0.024	0.407	0.024	0.026	0.025	0.217	0.024	0.026	0.025	0.217
t = 3	0.064	0.019	0.026	0.018	0.019	0.018	0.022	0.018	0.101	0.019	0.022	0.018	0.101
t = 4	0.053	0.005	0.012	0.019	0.013	0.019	0.007	0.012	0.215	0.013	0.007	0.012	0.215

## 6.6 Conclusions

Macroeconomic variables were added to the models of Chapter 5 in the expectation that they would reduce unobserved heterogeneity in the baseline hazard function, and hence improve the predictive power of the model. The in-sample fit of the models improved but there were no improvements in the out-of-sample prediction. This may be because the time-varying firm-specific information is sufficient for predicting financial distress. Alternatively it might be because there was insufficient coverage of the business cycle during the period of this study, or perhaps macroeconomic effects might be better captured by an exponentially weighted moving average.

This is one of relatively few studies to apply a non-linear approach in forecasting financial distress. In this chapter, a simple non-parametric method is developed following Loffler and Posch (2007), which allows for non-linearity between the response variable (the risk of financial distress) and the predictor variables. The empirical evidence confirms that when non-linearity is taken into account, both the explanatory and discriminatory power of the model improve considerably. However, the accuracy of the estimated probabilities of failure was not improved. Nonetheless, the improvement in discrimination suggests that a non-linear approach can make an important additional contribution to better failure prediction.

# **CHAPTER 7: CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH**

## **7.1 Summary of Findings**

This chapter recapitulates the set of research questions that have been raised throughout the thesis and forms conclusions based on these questions. The thesis sets out the following research issues:

- a) What are the problems of traditional financial distress models? How can the models be improved to perform better?
- b) How can the firm's changing probability of financial distress through time be modelled?
- c) Should corporate failure be considered as a sudden event or as a consequence of sustained decline in financial performance? Which approach is better to predict the outcome?
- d) Are accounting (financial statement) data sufficiently informative to measure the probability of financial distress? Are market-based variables more useful than accounting variables to predict financial distress?
- e) How can time-varying variables be utilised in distress prediction and do they increase predictive power?
- f) Do variables that reflect broad economic conditions add to predictive power in estimating the likelihood of corporate failure?

- g) Does allowing for a non-linear relation between predictor variables and the risk of financial distress improve predictions?

Based on the empirical findings of the thesis, using Australian data, the answers to these questions are summarised below.

What are the problems of traditional financial distress models? How can the models be improved to perform better? In this thesis, the absence of a time dimension was argued to be one of the key weaknesses in traditional financial distress models. Accordingly, incorporation of the dimension of time into model estimation, as well as formation of dynamic survival forecasts over time, were major objectives for this thesis. The process of moving from static to dynamic models began in Chapter 4 and continued through Chapters 5 and 6.

Traditional models use static data, typically one set of predictor variables observed at a fixed point in time before the onset of financial distress. The first task therefore was to allow for the predictors to be observed at multiple points in time as the firm moved towards financial distress. This was accomplished by studying a large sample of both healthy and distressed firms through time. Firms were followed over time until they either experienced financial distress or the study ended. Using the Cox hazards model it was possible to use all of the multiple years of data for all firms when estimating financial distress models. Chapter 4 empirically evaluated the effectiveness of the use of multiple-period data in predicting financial distress. The result showed that the use of all available firm-year observations to estimate the financial distress model led to a better out-of-sample prediction.

How can the firm's changing probability of financial distress through time be modelled? A natural technique to use in financial distress prediction is survival analysis. Survival analysis accounts for the lifetime (duration) of a firm's operation and keeps track of the changing probabilities of a firm's financial status as time passes. However, a number of approaches are possible in estimating survival models. A distinguishing feature of this thesis is the use of Cox regressions to estimate survival models and form dynamic forecasts of a firm's probability of financial distress. From Chapter 4 to Chapter 6, Cox hazards models were used and the predictive power of the Cox models were evaluated against the benchmark of the static logit model. Overall, the results of out-of-sample forecasts showed that the Cox model had superior predictive ability to the static logit model.

Should corporate failure be considered as a sudden event or as a consequence of sustained decline in financial performance? Which approach is better to predict the outcome? In Chapter 4, *Levels* and *Lagged Change Models* were constructed to examine the effects of lagged changes of predictor variables in predicting financial distress. A model with lagged changes in variables was found to provide a superior forecast to a model containing current level variables only. This implies that variables which reflect the financial trend of a company are likely to improve the predictive power of distress prediction models.

Are accounting (financial statement) data sufficiently informative to measure the probability of financial distress? Are market-based variables more useful than accounting variables to predict financial distress? This study examines the usefulness of equity price information in measuring the risk of financial distress. As shown in the

literature review, there have been divergent views on the role of accounting ratios in predicting financial distress. The empirical results in Chapter 4 support the use of both accounting and market variables. The results showed that market variables alone were not sufficient as an alternative to accounting ratios; instead, the predictive power of the financial distress model was maximised when both types of variables were combined together. This result remained consistent between the single-period and multiple-period models (where the latter model employs all available firm-year observations) and also across the *Levels* and *Lagged Change Models* (where the latter model allows for lagged variables).

How can time-varying variables be utilised in distress prediction and do they increase predictive power? The fifth question was one of the most challenging to tackle. Estimating the coefficients of predictor variables is not a problem when a Cox hazards model contains time-varying variables. However, when making forecasts of survival probabilities, the use of time-varying covariates causes a difficult problem in estimating the baseline hazard function. Chapter 5 overcomes this problem of making forecasts by implementing a procedure to estimate the integrated baseline hazard function. The model is capable of estimating the corresponding probability of the firm's failure at each point in time and of projecting the predictive failure probabilities as far as the out-of-sample data allow. In the out-of-sample forecast, the model shows reasonable predictive power (around 70% accurate based on the ROC curve). A logit model is used as a performance benchmark and the results suggest that the time-varying dynamic Cox model should be preferred.

Do variables that reflect broad economic conditions add to predictive power in estimating the likelihood of corporate failure? If the models had been estimated in calendar time the underlying economic conditions would be reflected in the baseline hazard. However, the models were estimated in event time and thus control for economic conditions can only be achieved by including macroeconomic variables in the model. This is done in Chapter 6. During the sample period examined, controlling for the state of the economy does not improve the predictive power of the model. The lack of significance of the macroeconomic variables may suggest that the firm-specific variables adequately reflected the economic conditions at the time the variables were observed. Alternatively, it may be that a longer time period is needed to capture the effects of macroeconomic variables.

Does allowing for a non-linear relation between predictor variables and the risk of financial distress improve predictions? Last but not least, the thesis also analysed the possible implication of a non-linear approach in forecasting financial distress. In Chapter 6, a non-parametric method of transforming the data was developed to capture the effect of non-linearity. The method was simple, but the impact on the prediction outcome was substantial. Allowing for non-linearity between the predictor variables and financial distress risk considerably increases predictive power. Indeed, it produced the model with the best prediction accuracy (approximately 80% accurate based on the ROC curve) in the thesis.

At the outset, the objective was to develop a financial distress model that could more accurately predict the risk of corporate failure. This has been achieved.

## 7.2 Contributions

The contribution of this thesis mainly lies in addressing the role of the time domain when forecasting financial distress. The application of a Cox proportional hazards model has been enhanced by the inclusion of time-varying variables and allowing the time-varying approach to run in event time with macroeconomic controls for calendar time effects.

A significant contribution of the thesis is overcoming the problem of making forecasts from a Cox hazards model when the model contains time-varying covariates. To the author's knowledge, this thesis is the first study to provide forecasts of survival probabilities using the Cox model with dynamic variables.

A further enhancement to the model was the incorporation of a non-linear approach. The use of the non-parametric data transformation results in a substantial increase in the power of the model to discriminate between financially distressed and non-distressed firms. The effect of non-linearity has received very little attention in the financial distress literature and the results of the thesis suggest that allowing for non-linearity may be one of the more promising ways of improving forecast accuracy.

In particular the thesis enriches the literature on financial distress prediction for Australian study. Most of financial distress studies to date use US bankruptcy data and the number of studies using Australian data is relatively small.

### **7.3 Limitations and Suggestions for Future Research**

This study uses the financial data observed as at the end of the financial year. By doing so, it facilitates the contemporaneous measurement of two different types of data, market data and accounting data. However, daily, monthly or quarterly-based data could be used for some variables.

Reliability of financial statement information, especially for those firms approaching financial distress, may also be an issue. It may, therefore, be worthwhile to include more market-driven variables such as past stock returns, and stock returns volatility, which can be observed more frequently than accounting data and are generally less subject to manipulation.

While the financial distress prediction study in this dissertation mainly focuses on the use of quantitative (financial) data, the study might be extended to incorporate qualitative information such as auditing quality and industry/business risk analysis, and also consider the role of management and its track record, such as management commitment, and management continuity.

It was expected that changing economic conditions would lead to unobserved heterogeneity in the baseline hazard. Macroeconomic variables were therefore added to the model to control for this unobserved heterogeneity. However this made no contribution to forecast accuracy. Lately, in the econometrics literature, there has been empirical work which estimates duration models with unobserved heterogeneity. Such work suggests the potential for nonparametric techniques in controlling for unobserved heterogeneity (Abbring and Van Den Berg, 2007; Bartolucci and Nigro,

2010; Briesch, Chintagunta, and Matzkin, 2010; Nicoletti and Rondinelli, 2010). This is a possible direction for future work in the financial distress literature.

Also, as suggested in Chapter 6, the testing of macroeconomic risk indicators might benefit from a longer sample period covering several business cycles.

Finally, the usefulness of the financial distress forecasts can be extended in other ways. For example, the survival method developed in this thesis for estimating financial distress can dovetail directly with the valuation of bonds. Having the survival probabilities ( $S_t$ ) as weights on contracted loan payments can help in estimating the expected value of a loan. In other words,  $S_t$  can be incorporated in the standard bond valuation formulae. However, it is noted that just weighting by  $S_t$  implies zero recovery in the event of default. Therefore, it would also be desirable to add in the estimated recovery in the event of default. This would simply be weighted by  $(1 - S_t)$ . Moreover, further extensions might be made from valuing loans to the margin on loans in order to determine their relative profitability.

## REFERENCE

- Abbring, J. H. and G. J. Van Den Berg, 2007, The unobserved heterogeneity distribution in duration analysis, *Biometrika* 94(1), 87-99.
- Agarwal, V., and R. Taffler, 2008, Comparing the performance of market-based and accounting-based bankruptcy prediction models, *Journal of Banking and Finance* 32, 1541-1551.
- Allison, P. D., 1984, *Event History Analysis*, Beverley Hills, Sage Publications.
- Altman, E. I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *The Journal of Finance* 23(4), 589-609.
- Altman, E. I., 2000, Predicting financial distress of companies: Revisiting the Z-score and Zeta Models, Working Paper, Stern School of Business, New York University.
- Altman, E. I., R. G. Haldeman, and P. Narayanan, 1977, Zeta™ analysis: A new model to identify bankruptcy risk of corporations, *Journal of Banking and Finance* 1, 29-54.
- Altman, E. I., G. Marco, and F. Varetto, 1994, Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience), *Journal of Banking and Finance* 18, 505-529.

- Andersen P. K., 1992, Repeated assessment of risk factors in survival analysis, *Statistical Methods in Medical Research* 1, 297-315.
- Atiya, A. F., 2001, Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results, *IEEE Transactions on Neural Networks* 12(4), 929-935.
- Australian Corporations Act, 2001, Available at:  
[http://www.austlii.edu.au/au/legis/cth/consol\\_act/ca2001172](http://www.austlii.edu.au/au/legis/cth/consol_act/ca2001172).
- Australian Securities Exchange, 2008, Listing Rules, Sydney, Australia, Available at:  
[http://www.asx.com.au/supervision/rules\\_guidance/changes/pre\\_20080331/listing\\_rules1.htm](http://www.asx.com.au/supervision/rules_guidance/changes/pre_20080331/listing_rules1.htm)
- Back, B., T. Laitinen, K. Sere, and M. V. Wezel, 1995, Choosing Bankruptcy Predictors using Discriminant Analysis, Logit Analysis and Genetic Algorithms, *Proceedings of the 1st International Meeting on Artificial Intelligence in Accounting, Finance and Tax*, 337-356.
- Baker, M. and J. Wurgler, 2002, Market timing and capital structure, *The Journal of Finance* 57, 1-32.
- Ball, R. and B. Phillip, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6(2), 159-178.
- Bandopadhyaya, A., 1994, An estimation of the hazard rate of firms under Chapter 11 protection, *The Review of Economics and Statistics* 76, 346-350.

- Bartolucci, F. and V. Nigro, 2010, A dynamic model for binary panel data with unobserved heterogeneity admitting a  $\beta$ -consistent conditional estimator, *Econometrica* 78(2), 719-733.
- Beaver, W. H., 1966, Financial ratios as predictors of failure, *Journal of Accounting Research* 4, 71-111.
- Beaver, W. H., M. F. McNichols, and J. Rhie, 2005, Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy, *Review of Accounting Studies* 10, 93-122.
- Begley, J., J. Ming, and S. Satts, 1996, Bankruptcy classification error in the 1980's: An empirical analysis of Altman's and Ohlson's models, *Review of Accounting Studies* 1, 267-284.
- Bellotti, T., and J. Crook, 2009, Credit Scoring with Macroeconomic Variables using Survival Analysis, *Journal of the Operational Research* 60, 1699-1707.
- Berger, P., E. Ofek, and I. Swary, 1996, Investor valuation of the abandonment option, *Journal of Financial Economics* 42, 257-287.
- Blum, M., 1974, Failing company discriminant analysis, *Journal of Accounting Research* 12, 1-25.
- Bonfim, D., 2009, Credit risk drivers: evaluating the contribution of firm level information and of macroeconomic dynamics, *Journal of Banking and Finance* 33, 281-299.

- Briesch, R. A., P. K. Chintagunta and R. L. Matzkin, 2010, Nonparametric discrete choice models with unobserved heterogeneity, *Journal of Business & Economic Statistics* 28(2), 291-307.
- Cadden, D., 1991, Neural networks and the mathematics of chaos – an investigation of these methodologies as accurate predictions of corporate bankruptcy, *The First International Conference on Artificial Intelligence Applications on Wall Street*, IEEE Computer Society Press, New York.
- Campbell, J., J. Hilscher, and J. Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899-2939.
- Carling, K., T. Jacobson, J. Linde, and K. Roszbach, 2007, Corporate credit risk modeling and the macroeconomy, *Journal of Banking and Finance* 31, 845-868.
- Castagna, A. D., and Z. P. Matolcsy, 1981, The prediction of corporate failure: Testing the Australian experience, *Australian Journal of Management* 6, 23-50.
- Chan, H., R. Faff, P. Gharghori, and P. Lajbcygier, 2008, Default risk modeling: A new non-linear approach, Working Paper, University of Melbourne and Monash University
- Chava, S., and R. Jarrow, 2004, Bankruptcy prediction with industry effects, *Review of Finance* 8, 609-641.

- Chen, K. C., and C. J. Lee, 1993, Financial ratios and corporate endurance: A case of the oil and gas industry, *Contemporary Accounting Research* 9(2), 667-694.
- Chen, L., M. Yen, H. Wu, C. Liao, D. Liou, H. Kuo, and T. H. Chen, 2005, Predictive survival model with time-dependent prognostic factors: development of computer-aided SAS Macro program, *Journal of Evaluation in Clinical Practice* 11(2), 181-193.
- Coats, P. K., and L. F. Fant, 1992, A neural network approach to forecasting financial distress, *The Journal of Business Forecasting* 3(4), 9-12.
- Coats, P. K., and L. F. Fant, 1993, Recognising financial distress patterns using a neural network tool, *Financial Management* 22(3), 142-155.
- Cole, R. A., and Q. Wu, 2009, Predicting bank failures using a simple dynamic hazard model, *The 22nd Australasian Finance and Banking Conference*, Sydney.
- Cox, D. R., 1972, Regression and life tables, *Journal of the Royal Statistical Society* 34, 187-220.
- Crapp, H., and M. Stevenson, 1987, Development of a method to assess the relevant variables and the probability of financial distress, *Australian Journal of Management* 12(2), 221-236.
- Cybinski, P., 2001, Description, explanation, prediction – the evolution of bankruptcy studies?, *Managerial Finance* 27, 29-44.

- Deakin, E. B., 1972, A discriminant analysis of predictors of business failure, *Journal of Accounting Research* 10, 167-179.
- deListed (2006) *Delisted Companies*, NSW, Australia, Available at:  
<http://www.delisted.com.au/>.
- Dichev, I., 1998, Is the risk of bankruptcy a systematic risk?, *The Journal of Finance* 53, 1131-1147.
- Dimitas, A. I., S. H. Zanakis, and C. Zopounidis, 1996, A survey of business failures with an emphasis on prediction methods and industrial applications, *European journal of Operational Research* 90, 487-513.
- Disney, R., J. Haskel, and Y. Haden, 2003, Entry, exit and establishment survival in UK manufacturing, *The Journal of Industrial Economics* 51(1), 91-112.
- Drapeau, R., 2004, *Bankruptcy prediction model using discriminant analysis on financial ratios derived from corporate balance sheets*, Doctoral Dissertation, Lamar University, Australia.
- Faulkender, M., and M. A. Petersen, 2005, Does the source of capital affect capital structure?, *Review of Financial Studies* 19, 45-79.
- Flynn, E., and G. Bermant, 2004, Bankruptcy by the numbers, Working Paper, Executive Office for the United States Trustees, Burke Virginia.

- Ford, B., and K. Taylor, 2005, Recent developments in Australian bond yields, *Economic Round-up*, Spring 2005, 111-120.
- Foster, G., 1986, *Financial Statement Analysis*, Prentice Hall, New Jersey.
- Frydman, H., E. I. Altman, and D. Kao, 1985, Introducing recursive partitioning for financial classification: The case of financial distress, *The Journal of Finance* 40(1), 269-291.
- Geman, S., E. Bienenstock, and T. Dousat, 1992, Neural networks and the bias/variance dilemma, *Neural Computation* 5, 1-58.
- George, C. R., J. D. Spiceland, and S. L. George, 1996, A longitudinal study of the going-concern audit decision and survival time, *Advances in Quantitative Analysis of Finance and Accounting* 4, 77-103.
- Gharghori, P., H. Chan, and R. Faff, 2006, Investigating the performance of alternative default-risk models: Option-based versus accounting-based approaches, *Australian Journal of Management* 31, 207-234.
- Grice, J. S., and M. T. Dugan, 2001, The limitations of bankruptcy prediction models: Some cautions for the researcher, *Review of Quantitative Finance and Accounting* 17, 151-166.
- Grice, J. S., and R. W. Ingram, 2001, Tests of the generalisability of Altman's bankruptcy prediction model, *Journal of Business Research* 54(1), 53-61.

- Hamerle, A., T. Liebig, and D. Rösch, 2003, Benchmarking asset correlations, *Risk* 16, 77-81.
- Han, B., R. Jennings and J. Noel, 1992, Communication of non-earnings information at the financial statements release date, *Journal of Accounting and economics* 15, 63-86.
- Hawley, D. D., J. D. Johnson, and D. Raina, 1990, Artificial neural systems: A new tool for financial decision-making, *Financial Analysts Journal* 46, 63-72.
- Helwege, J. 1996, Determinants of savings and loan failures: Estimates of a time-varying proportional hazard function, *Journal of Financial Services Research* 10, 373-392.
- Hill, N. T., S. E. Perry, and S. Andes, 1996, Evaluating firms in financial distress: An event history analysis, *Journal of Applied Business Research* 12(3), 60-71.
- Hillegeist, S. A., E. K. Keating, D. P. Cram, and K. G. Lundstedt, 2004, Assessing the Probability of Bankruptcy, *Review of Accounting Studies* 9, 5-34.
- Jones, S., and D. A. Hensher, 2004, Predicting firm financial distress: A mixed logit model, *The Accounting Review* 79(4), 1011-1038.
- Kane, G. D., F. M. Richardson, and P. Graybeal, 1996, Recession-induced stress and the prediction of corporate failure, *Contemporary Accounting Research* 13, 631-650.

- Karels, G. V., and A. Prakash, 1987, Multivariate normality and forecasting of business bankruptcy, *Journal of Business Finance and Accounting* 14(4), 573-593.
- Karfakis, C., and A. Phipps, 1996, Treasury note and bank bill rates, the risk premium and Australian monetary policy, *Australian Economic Paper* 35, 321-333.
- Kent, C., and P. D'Arcy, 2001, Cyclical prudence and credit cycles in Australia, in *BIS Papers* 1, 58–90, March, Basel.
- Kim, Y., D. R. Anderson, T. L. Amburgey, and J. C. Hickman, 1995, The use of event history analysis to examine insurer insolvencies, *Journal of Risk and Insurance* 62, 94-110.
- Koh, H. C., 1992, The sensitivity of optimal cut-off points to misclassification costs of Type I and Type II errors in the going-concern prediction context, *Journal of Business Finance and Accounting* 19, 187-197.
- Lane, W. R., S. W. Looney, and J. W. Wansley, 1986, An application of the Cox proportional hazards model to bank failure, *Journal of Banking and Finance* 10(4), 511-531.
- LeClere, M. J., 2000, The occurrence and timing of events: Survival analysis applied to the study of financial distress, *Journal of Accounting Literature* 19, 158-189.
- Li, K., 1999, Bayesian analysis of duration models: an application to Chapter 11 bankruptcy, *Economics Letters*, 63, 305-312.

- Liu, J., 2004, Macroeconomic determinants of corporate failures: evidence from the UK, *Applied Economics* 36, 939-945.
- Löffler, G., and P. N. Posch, 2007, *Credit risk modeling using Excel and VBA*, John Wiley and Sons, Inc., New York.
- Mason, S. J., and N. E. Graham, 1999, Conditional probabilities, relative operating characteristics, and relative operating levels, *Weather and Forecasting* 14(5), 713-725.
- Merton, R. C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *The Journal of Finance* 29, 449-470.
- Nam, C., T. Kim, N. Park, and H. Lee, 2008, Bankruptcy prediction using a discrete-time duration model incorporating temporal and macroeconomic dependencies, *Journal of Forecasting* 27, 493-506.
- Nicoletti, C. and C. Rondinelli, 2010, The (mis)specification of discrete duration models with unobserved heterogeneity: A Monte Carlo study, *Journal of Econometrics* 159, 1-13
- Nothman, P., 1993, *Record of Liquidations and Receiverships*, Financial Analysis Publications, Sydney, NSW.
- Odom, M. D., and R. Sharda, 1990, A neural network model for bankruptcy prediction, *Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN)* 2, 163-168.

- Ohlson, J. A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18(1), 109-131.
- Oxelheim, L., and C. Wihlborg, 2008, Corporate distress and restructuring with macroeconomic fluctuations: The cases of GM and Ford, *IFN Working Paper*, No. 780.
- Pacey, J. W., and T. M. Pham, 1990, The predictiveness of bankruptcy models: methodological problems and evidence, *Australian Journal of Management* 15(2), 315-337.
- Parker, S., G. F. Peters, and H. F. Turetsky, 2002, Corporate governance and corporate failure: A survival analysis, *Corporate Governance* 2(2), 4-12.
- Partington, G., P. Russel, M. Stevenson, and V. Torbey, 2001, Predicting return outcomes to shareholders from companies entering chapter 11 bankruptcy, *Managerial Finance* 27, 78-96.
- Pesaran, H. H., T. Schuermann, B. Treutler, S. M. Weiner, 2006, Macroeconomic dynamics and credit risk: A global perspective, *Journal of Money, Credit and Banking* 38 (5), 1211-1262.
- Raghupathi, W., L. L. Schkade, and B. S. Raju, 1991, A neural network application for bankruptcy prediction, *Proceedings of the Twenty-Fourth Annual Hawaii International Conference on IEEE* 4, 147-155.

- Rajan, R. G., and L. Zingales, 1995, What do we know about capital structure? Some evidence from international data, *The Journal of Finance* 50, 1421-1460.
- Reisz, A., and C. Perlich, 2004, A market-based framework for bankruptcy prediction, Working paper, Baruch College, City University of New York.
- Richardson, F. M., G. D. Kane, and P. Lobingier, 1998, The impact of recession on the prediction of corporate failure, *Journal of Business Finance and Accounting* 25, 167-186.
- Rösch, D., and H. Scheule, 2004, Forecasting retail portfolio credit risk, *Journal of Risk Finance* 5(2), 16-32.
- Rosch, D. and H. Scheule, 2005, A multi-factor approach for systematic default and recovery risk, *The Journal of Fixed Income* 15, 63-75.
- Rose, P. S., W. T. Andrews, and G. A. Giroux, 1982, Predicting business failure: A macroeconomic perspective, *Journal of Accounting, Auditing & Finance* 6, 20-31.
- Rudorfer, G., 1995, Early bankruptcy detection using neural networks, *Proceedings of the International Conference on Applied Programming Languages* 25(4), 171-178.
- Serrano, C. C., 1997, Feed forward neural networks in the classification of financial information, *European Journal of Finance* 3, 183-202.

- Sharma, D. S., 2001, The role of cash flow information in predicting corporate failure: The state of the literature, *Managerial Finance* 27(4), 3-28.
- Shumway, T., 2001, Forecasting bankruptcy more accurately: A simple hazard model, *The Journal of Business* 74, 101-124.
- Sloan, R. G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289-315.
- Sobehart, J. R., and R. M. Stein, 2000, Moody's public firm risk model: A hybrid approach to modelling short term default risk, *Moody's Rating Methodology*.
- Standard and Poor's 2002, *Standard & Poor's Announces Changes to the S&P Indices*, Press Release, July.
- Stickney, C. P. 1996, *Financial Reporting and Statement Analysis*, 3rd Edition. Forth Worth: The Dryden Press.
- Tam, K. Y., and M. Y. Kiang, 1992, Managerial applications of neural networks: The case of bank failure predictions, *Management Science* 38, 926-947.
- Vassalou, M., and Y. Xing, 2004, Default risk in equity returns, *The Journal of Finance* 59 (2), 831-868.
- Viney, C., 2003, *Financial Institutions, Instruments, and Markets*, 4<sup>th</sup> Edition, McGraw-Hill, Australia.

- Wadhvani, S. B., 1986, Inflation bankruptcy, default premia and the stock market, *Economic Journal*, 96, 120–138.
- Whalen, G., 1991, A proportional hazards model of bank failure: An examination of its usefulness as an early warning model tool, *Economic Review*, Federal Reserve Bank of Cleveland, 21-31.
- Wheelock, D. C., and P. W. Wilson, 1995, Explaining bank failures: Deposit insurance, regulation, *Review of Economics & Statistics* 77, 689-700.
- Wheelock, D. C., and P. W. Wilson, 2000, Why do banks disappear? The determinants of U.S. bank failures and acquisitions, *Review of Economics and Statistics* 81, 127-138.
- Wilson, R. L., and R. Sharda, 1994, Bankruptcy prediction using neural networks, *Decision Support Systems* 11, 545-557.
- Wong, B., G. Partington, M. Stevenson, and V. Torbey, 2007, Surviving chapter 11 bankruptcies: Duration and payoff?, *ABACUS* 43(3), 363-387.
- Zavgren, C. V., 1985, Assessing the vulnerability to failure of American industrial firms: A logistic analysis, *Journal of Business Finance and Accounting* 12, 19-46.
- Zhang, G., M. Y. Hu, B. E. Patuwo, and D. C. Indro, 1999, Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis, *European Journal of Operational Research* 116, 16-32.

Zopounidis, C., 1987, A multicriteria decision making methodology for the evaluation of the risk of failure and an application, *Foundations of Control Engineering* 12, 45-67.

# APPENDIX A: SAS MACRO PROGRAM FOR THE TIME-VARYING COX HAZARDS MODEL ESTIMATION

```

DM "CLEAR LOG; CLEAR OUTPUT";

%LET AUTHOR = Maria H. Kim ;
%LET UPDATED = 30 Oct 2008 ;

LIBNAME AF_estim "C:\maria_work\current_work\my_research_2008\TVC(Oct_2008)\5_estimation";

%LET ProgName = "E_Main_efron_final.sas" ;
%LET ProgPath = C:\maria_work\current_work\my_research_2008\TVC(Oct_2008)\5_estimation ;
%LET ProgDesc = Cox proportional hazard model with time-varying covariates ;

TITLE "&ProgDesc";

%LET Obs_Limit = MAX ;
*****
* PART 1 - SAS Macro program for time-varying survival model
*****
*****
* 1.1 The program starts from a macro statement denoted as cov_array, which declares a series of
* repeated measurement (&n_rm) for each time-varying covariate in array format.
*****
%macro cov_array;
  %do i=1 %to &n_cov;
    array yy&i.(*) x&i._1-x&i._&n_rm1;
  %end;
%mend cov_array;
*****
* 1.2 Macro cov_last creates pseudo-covariate (y&i) for the last updated covariate (yy&i.(j))
* before each survival time.
*****
%macro cov_last;
  %do i=1 %to &n_cov;
    y&i=yy&i.(j);
  %end;
%mend cov_last;

```

```

*****;
* 1.3 Macro time-missing creates pseudo-time update variable for cases with missing covariates from ;
* the last time to actual survival time by appending last updated time-varying covariate values ;
* until actual survival time (stime). For example, suppose a firm has the financial records of ;
* Total Assets at 1,2,3 year and survives until the end of year 4, the macro program time-missing;
* creates pseudo-time variable (timet(&k)) and pseudo-covariate (x&i_&k) which assumes the value ;
* of Total Assets at year 3 representing the recorded value between year 3 and 4. ;
*****;
□ %macro time_missing;
  %do k=2 %to &n_rm1;
    %let kk=%eval(&k-1);
    if timet(&k)=. and timet(&kk)^=. and timet(&kk)^=stime then timet(&k)=stime;

    %do i=1 %to &n_cov;
      if timet(&k)^=. and x&i_&k=. then x&i_&k=x&i_&kk;
    %end;
  %end;
%mend time_missing;
-----
*****;
* 1.4 Macro allcov_matrix declares all time-varying covariates matrix form for covariate in ;
* matrix form. ;
*****;
□ %macro allcov_matrix;
  xmatrix=J(&n_rm1,&n_cov,.);
  %do i=1 %to &n_cov;
    xmatrix[,&i]=(x&i.[&predobs,])`;
  %end;
%mend allcov_matrix;
-----

```

```

*****;
* 1.5 Macro predict_time generates predicted cumulative survival with regular time interval.      ;
* The program consists of two parts.                                                         ;
* The first part deals with the sortation of empirical survival time (tt).                   ;
* The second part declares a matrix including four columns,                                  ;
* the first for the predictive time (oo[1]),                                                ;
* the second for the calculation of cumulative survival (surv) (oo[2]),                       ;
* the third for the time-varying risk score (oo[3]) and                                     ;
* the last for the cumulative hazard function estimate (oo[4]).                             ;
*****;
%macro predict_time(f);
  loctt=(loc(tt))`;      rtt=nrow(loctt);
  tt1=J(1,rtt+1,0);
  do i=2 to rtt+1;
    tt1[i]=tt[loctt[i-1]];
  end;
  tt2=tt1;
  tt1[,rank(tt1)]=tt2;
  call quad(z,"&f",tt1);
  rtt1=ncol(tt1);
  ttn=J(rtt1-1,1,0);
  do i=2 to rtt1;
    ttn[i-1]=tt1[i];
  end;

  oo=J(1,4,.);
  do cc=&start to &stop by &stin until(stime[rec]<cc+1);
    if cc=0 then oo[3]=0;
    if cc>0 then oo[3]=fun_s(cc);
    crit=cc;
    index=(ttn<=crit);
    high=sum(z#index);
    print z index high;
    surv=exp(-high);
    oo[1]=crit; oo[2]=surv; oo[4]=high;
    if cc=0 then predict=oo;
    if cc>0 then predict=predict/oo;
  end;
%mend predict_time;
*****;
* 1.6 Macro program phreg_m was to produce regression coefficients for time-varying covariates. ;
* Parameters used in Macro program include dataset (mydata), actual survival time (stime),    ;
* censored status (fail), number of covariates (n_cov), maximum number of repeated measurement ;
* rescaled function of prognostic score (transfun), and allocation of symbol space (ssize).    ;
*****;
%macro phreg_m(mydata,stime,fail,n_cov,n_rm,transfun,ssize);

%let n_rm1=%eval(&n_rm+1);

data AF_estim.pred AF_estim.missrep;
  set &mydata end=stop;

  stime=&stime;
  fail=&fail;

  array timet(*) time1-time&n_rm1;
  %cov_array;
  %time_missing;

*****;
* These statements report number of observed cases with complete missing value of time-varying ;
* covariates at all survival times (n_miss) and delete these cases in the following estimation. ;
*****;
withmiss=(sum(x1_1-x&n_cov_1)=.);
if _n_=1 then n_miss=0;
n_miss+(withmiss=1);

output AF_estim.pred;
if stop=1 then output AF_estim.missrep;

data AF_estim.pred1;
  set AF_estim.pred;

if withmiss=1 then delete;

proc sort;
  by stime;
run;

```

```

*****;
*   The following statements estimate regression coefficient for corresponding time-varying covariate ;
*   declared in Macro cov_array. All estimates of regression coefficients were stored as dataset beta. ;
*****;
proc phreg data=AF_estim.pred1 outest=AF_estim.efron_beta;
  model stime*fail(0)= y1-y&n_cov/r1 GCONV=1E-15 ties = efron;
  array timet(*) time1-time&n_rm1;
  %cov_array;

*****;
*   The comparison between survival time (stime) and time at measurement (timet) of time-varying ;
*   covariate, the updated value produced from Macro cov_last. ;
*****;
  do j=1 to &n_rm1;
    if stime ge timet(j) and timet(j) ne . then do;
      %cov_last;
    end;
  end;
run;
*****;
*   The following statements apply SAS IML language to calculate integrated baseline hazard, ;
*   HO(t) and hazard rate, hO(t). ;
*   The first part of statement is pertinent to the preparation of data on relevant variables ;
*   used for calculating time-varying scoring system. ;
*****;
proc iml symsize=&ssize;

  /* Data preparation */
  use AF_estim.pred1;
  read all var (stime)           into stime ;
  read all var (fail)            into fail  ;
  read all var ("time1 " : "time&n_rm1 ") into time ;

  /* Input of time-varying covariates */
  %do i=1 %to &n_cov;
    read all var("x&i._1" : "x&i._&n_rm1") into x&i;
  %end;

  /* Input of regression coefficient */
  use AF_estim.efron_beta;
  read all var ("y1" : "y&n_cov") into efron_beta;

  /* Number of cases with complete missing data on time-varying covariates */
  use AF_estim.missrep;
  read all var (n_miss) into n_miss;

  /* Number of patients */
  m=nrow(stime);
  tss={ 0 0 } ;

```

```

*****;
*   According to Andersens equation, the following program is to calculate integrated      ;
*   baseline hazard.                                                                    ;
*****;
do k=1 to m;
  if fail[k]=1 then do;
    score=0; tss0=J(1,2,0);
    do i=k to m;
      do j=1 to &n_rm1;
        if stime[k] >= time[i,j] & time[i,j] ^= . then do;
          %do p=1 %to &n_cov;
            yy=p*x&p[i,j];
          %end;
        end;
      end;

      xx=0;
      %do p=1 %to &n_cov;
        xx=xx+yy&p*efron_beta[&p];
      %end;

      score=score+exp(xx) ;
    end;
    print score;
    tss0[1]=stime[k]; tss0[2]=1/score;
    tss=tss//tss0;
  end;
end;

```

```

*****;
* Similarly, the estimation of baseline hazard function h0(t) is also programmed as follows. ;
*****;
rowtss=nrow(tss);
xtss=J(1,2,0);
do i=2 to rowtss-1;
    if tss[i+1,1]>tss[i,1] then xtss=xtss//tss[i,];
end;

xtss=xtss//tss[rowtss,];

rowxtss=nrow(xtss); ntss=xtss;
do i=1 to rowxtss-1;
    ntss[i+1,2]=xtss[i+1,2]/(xtss[i+1,1]-xtss[i,1]);
end;
print ntss;
* print rowtss rowxtss tss xtss ntss;

*****;
* Programming for calculating time-varying score (score [i,j]) for empirical data is ;
* illustrated in the following statements. ;
*****;
rtss=nrow(ntss);

*print ntss;
score=J(m,&n_rm1,.);
do i=1 to m;
    do j=1 to &n_rm1;
        score[i,j]=0;
        %do p=1 %to &n_cov;
            score[i,j]=score[i,j]+x&p[i,j]*efron_beta[&p];
        %end;
    end;
end;

start fun_s(t) global(ntss,rtss,rec,time,score);
    xscore=0;
    do i=1 to &n_rm1-1 until(time[rec,i+1]=.);
        if time[rec,i]<=t then xscore=score[rec,i];
    end;
    if time[rec,&n_rm1]<=t & time[rec,&n_rm1]^= . then xscore=score[rec,&n_rm1];
*print t xscore;
    &transfun;
    return(outscore);

finish;

*****;
* These statements are to calculate predicted hazard rate (hh) using predicted time-varying score. ;
*****;
start fun(t) global(ntss,rtss,rec,time,score);
    xscore=0;
    do i=1 to &n_rm1-1 until(time[rec,i+1]=.);
        if time[rec,i]<=t+i then xscore=score[rec,i];
    end;
    %if time[rec,&n_rm1]<=t & time[rec,&n_rm1]^= . then xscore=score[rec,&n_rm1];
*print t xscore;
    do i=1 to rtss-1;
        if ntss[i,1]<=t then hh=ntss[i+1,2]*exp(xscore);
    end;
*print hh;
    return(hh);
finish;

print / "Note: Number of deletion because of at least one missing or invalid values on the initial
covariates:",
n_miss;

%mend phreg_m;

```

```

*****;
* 1.7 Macro program for individual prediction of cumulative survival given time-varying score is ;
* illustrated in the following statement. Notations are explained as follows. ;
* predobs: number of observations will be predicted ;
* n_cov: the same as defined in PHREG_M ;
* n_rm: the same as defined in PHREG_M ;
* tstart: the beginning of the predicted period ;
* tstop: the end of the predicted period ;
* tinv: time lag between reported time points ;
*****;

/* Specify survival time and number of repeated measurement for a selected individual */
%macro pred(predobs,n_cov,n_rm,tstart,tstop,tinv) ;

  %let n_rml=%eval(&n_rm+1) ;

  ptt=time[&predobs,]`;

  %allcov_matrix;

  * print / "Observation: &predobs" ptt xmatrix;

  /* Prediction of cumulative survival */
  do rec=&predobs to &predobs;
    tt=tss[,1]//(time[rec,])`;

    %predict_time(fun);

    xstime=stime[rec]; xfail=fail[rec];

    pred_c=( time p_survival risk_score cum_hazard ) ;

    print / rec xstime xfail predict[c=pred_c];
  end;
  create AF_estim.efron&predobs from predict[colname=pred_c];
  append from predict;

%mend pred;
quit;

/* Create proportional hazard model by different time-varying covariates */
%phreg_m(mydata=AF_estim.rename_asx,time=time,fail=fail,n_cov=7,n_rm=8,ssize=300,
transfun= outscore=xscore );

/* Prediction for the tenth subject */
%pred(predobs=380,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=381,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=382,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=383,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=384,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=385,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=386,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=387,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=388,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=389,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=390,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=479,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=513,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=521,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=660,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=745,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=800,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=807,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=901,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=993,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=996,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1000,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1040,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1074,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1103,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1155,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1199,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1206,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
%pred(predobs=1262,n_cov=7,n_rm=8, tstart=0, tstop=10, tinv=1);
quit;

```

# APPENDIX B: SAS MACRO PROGRAM FOR MODEL EVALUATION OF PREDICTIVE ACCURACY USING RECEIVER OPERATING CHARACTERISTICS CURVE

```

DM "CLEAR LOG; CLEAR OUTPUT";

%LET AUTHOR = Maria H. Kim ;
%LET UPDATED = 04 Nov 2008 ;

LIBNAME AF_hold1 "C:\maria_work\current_work\my_research_2008\TVC(Oct_2008)\6.1_validation_baseline_corrected";

%LET ProgName = "h_validation_efron.sas" ;
%LET ProgPath = C:\maria_work\current_work\my_research_2008\TVC(Oct_2008)\6.1_validation_baseline_corrected;
%LET ProgDesc = Cox proportional hazard model with time-dependent covariates ;

TITLE "&ProgDesc";

%LET Obs_Limit = MAX ;
*****
* PART 2 - SAS Macro program for model evaluation of predictive accuracy using ROC
*****

*****
* 2.1 This section shows the SAS code for model evaluation with receiver operating characteristics
* (ROC) curve in one macro statement named 'ROC'. Parameters include:
* n_cov: the same as defined in 'PHREG_M'
* n_rm: the same as defined in 'PHREG_M'
* ptime: predictive time from the starting point where t = 0
* lower: smallest value of tested cut-off point of risk score
* upper: largest value of tested cut-off point of risk score
* rocint: incremental unit between 'lower' and 'upper'
* transfun: the same as defined in 'PHREG_M'
*****
%macro roc(n_cov,n_rm,ptime,lower,upper,rocint,transfun);
title Predict time: &ptime years, cut-off point: &lower ~ &upper;
%let n_rm1=%eval(&n_rm+1);

*****
* Merge empirical data (pred) with data set efron_beta containing regression coefficients
* estimated in Cox hazards model.
*****
data AF_hold1.vv_efron;
set AF_hold1.pred;
if _n_ = 1 then merge AF_estim.efron_beta;

*****
* The following statements declare the event as censored status if survival time is less than
* the predictive time.
*****
event=fail;

if stime>&ptime then event=0;
if fail=0 and stime<&ptime then delete;

%let n_rm1=%eval(&n_rm+1);

```

```

*****;
*   The following statements give each firm the updated risk score no later than the predictive   ;
*   time according to the built Cox hazards model in 'PHREG_M'.                               ;
*****;
%macro htov;
  %do j=1 %to &n_rml;
    if &ptime>=times&j>0 then do;
      xscore=0;
      %do k=1 %to &n_cov;
        xscore=xscore+y&k*x&k._&j;
      %end;
    end;
  %end;
  &transfun;
%mend htov;

%htov;
if outscore=. then delete;
run;

proc sort;
  by stime;
run;

proc iml;
  use AF_hold1.vv_efron;
  read all var (outscore) into outscore;
  read all var (event) into event;

*****;
*   Variables dp and dn give the number of event and censoring before the predictive time.       ;
*   This is to calculate of sensitivity and specificity for the ROC curve.                     ;
*****;
dp=sum(event=1);
dn=sum(event=0);

*****;
*   The vector of 'CRIT' is composed of different cut-off points of risk score. Accordingly, the   ;
*   results of test based on the given cut-off point can be determined. Therefore, sensitivities  ;
*   and specificities in those different cut-off points can be calculated.                   ;
*****;
crit=(do(&lower, &upper, &rocint))`;
m=nrow(crit);
sen=J(m,1,.); onemspe=J(m,1,.);
do i=1 to m;
  sen[i] =sum(event=1 & (outscore> crit[i]) )/dp;
  onemspe[i]=sum(event=0 & (outscore> crit[i]) )/dn;
end;

*****;
*   The following statements give the result of area under the ROC curve.                     ;
*****;
area=0;
do i=1 to m-1;
  area=area+( (sen[i]+sen[i+1])*(onemspe[i]-onemspe[i+1])/2 );
end;

print area;

out=crit||sen||onemspe;
head=(criteria sen OneMSpe);
  create AF_hold1.efron_plot from out[colname=head];
  append from out;
quit;

proc print data=AF_hold1.efron_plot;
run;

```

```

*****;
*   The following statements are for the graph of ROC curve drawn automatically in SAS.   ;
*****;
proc gplot data=AF_hold1.efron_plot;
  plot sen*onemspe;
  symbol1 interpol=join ci=blue value=dot height=1 cv=red;
run;
quit;
%mend roc;

/* Test what range of cut-off point makes sen & spe between 0 and 1 */
%roc(n_cov=7,n_rm=4,ptime=1 ,lower=-10,upper=11,rocint=0.5,
transfun= outscore=xscore; );
%roc(n_cov=7,n_rm=4,ptime=2 ,lower=-10,upper=11,rocint=0.5,
transfun= outscore=xscore; );
%roc(n_cov=7,n_rm=4,ptime=3 ,lower=-10,upper=11,rocint=0.5,
transfun= outscore=xscore; );
%roc(n_cov=7,n_rm=4,ptime=4 ,lower=-10,upper=11,rocint=0.5,
transfun= outscore=xscore; );

```